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Relational Information Theory

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Submitted for the degree of Doctor of Philosophy

University of Sussex, August 2017

Declaration

I hereby declare that this thesis has not been and will not be submitted in whole or in part to another University for the award of any other degree.

Signature:

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RELATIONAL INFORMATION THEORYSUMMARY

“Pseudodiagnostic” patterns of information search were first classified by Doherty et al. (1979), predicated on their assertion that only the selection of data that allow for the calculation of Bayesian probability ratios may be considered rational. However, with the exception of Crupi et al. (2009), who have argued for an epistemological explanation loosely based on the de Finetti theorem of exchangeable probability assignments (see, eg., Heath and Sudderth, 1972), the Doherty et al. interpretation of information search patterns has gone unchallenged.

This thesis seeks to answer three questions: can people make reasonable inferences from probabilistic information; is there an identifiable common approach to information selection; and, if not Bayes’ theorem, then what mathematics might underlie human decision-making?

A series of experiments demonstrate that people appear to select data not only for their ordinal values, but also to establish the relationships between them. However, since such a holistic approach to decision-making lies beyond the scope of the naïve Bayes’ classifier, an alternative expression for the calculation of likelihood ratios is

presented. By rejecting the Kolmogorov axioms of classical statistics in favour of the von Neumann mathematical axioms of quantum mechanics, it is shown that not only may probabilistic information be reconceptualised as isomorphic representations of quantised and entangled statistical systems, but that it is only this approach which allows for the assumption free calculation of likelihood ratios. Further, the mathematical derivation demonstrates that Bayes' theorem is a special case of this more general quantum expression, applicable only where the conditional independence of data is guaranteed. Mathematical modelling, combined with the results of another experiment, is used to investigate the plausibility of this expression as an explanation for both information search patterns, and people's estimation of probability.

The nature of this "relational information theory" is both discussed and situated within the wider psychological field of mental models.

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In memory of my father,

Dr. Gwynfryn George Bond, B.Sc., Ph.D., C.Eng., I.E.E.E.
(1928 — 2009)

I think he might have been surprised.

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Chapter 1

Introduction

This thesis considers the subject of diagnostic decision-making, concerning itself with two central issues of ordinal decision-making and the estimation of likelihood within a Bayesian framework. To date, decision-making research has fallen into broad categories of normative and descriptive theories, where normative theories, such as Subjective Expected Utility (Savage, 1954), aim to show how decisions should be reached and descriptive theories, such as Prospect Theory (Kahneman and Tversky, 1979) describing how decisions are actually made.

Research based on Bayes' theorem has identified two primary psychological effects of “base rate neglect” and “confirmation bias”, with both phenomena being used to support the notion that humans are illogical. Within a Bayesian epistemological framework it is possible to reconcile such cognitive phenomena with classical decision-making theory because of the conditionalisation of prior probabilities on the subjective posterior probability distributions. Since these distributions are updated by the rational decision-maker following the introduction of new evidence (Talbot, 2016), there is a consequential change in degree of belief which may lead to apparent violations of logical deductive inference from a frequentist view of the laws of probability. Such behaviour may be seen, for instance, in the running of “Dutch books” where bets may be accepted which, purely on the base of frequentist probability, are almost certain to be lost (see, e.g., Milne, 1997). However, such a defence of human rationality is predicated upon the belief that this conditionalisation will lead to an epistemically good outcome (Greaves and Wallace, 2006).

There are alternative views. For instance, Kahneman and Tversky (1973) cite an experiment in which participants decided whether brief personality sketches were more likely to be those of engineers or lawyers. Despite being told the relative percentages of the two groups, they found that the prior probabilities were ignored with the participants relying upon their own internal representations to make an evaluation of likelihood. For Kahneman and Tversky such base rate neglect is evidence of a representativeness heuristic in which there is a tendency to assess the probability that a stimulus belongs to a particular class by judging the degree to which the event corresponds to an appropriate mental model. While base rate neglect has also been found by a number of other researchers (see, e.g., Doherty et al., 1979), there is evidence that the effect is dependent upon task framing. For instance, Gigerenzer et al. (1988) found that when the participants themselves generated the prior information the base rate neglect effect disappeared. Indeed, Gigerenzer et al. suggest that this self-generation of data encourages the participants to represent the problem in terms of Bayesian revision. Equally, the phenomenon of confirmation bias arises from a tendency to consider only one possible interpretation of information, i.e., to consider the likelihood of only one possible decision. There is support for this view. When Kern and Doherty (1982) asked medical students to select information that would help them choose between two diagnoses for patients, their results showed that 83% of the participants failed to select data with the potential to nullify a diagnosis, instead preferring to choose information relating to just one outcome. This finding is at odds with the principle of “falsification”, where data should be selected to disprove a hypothesis (see, e.g., Guala, 2000), but is entirely consistent with findings drawn from the Wason selection task (Wason, 1968). Mynatt et al. (1993) speculate that this tendency may result from the capacity limitations of working memory.

Chapter 2 investigates the “pseudodiagnosticity” paradigm. Derived from the work of Doherty et al. (1979) into base rate neglect and confirmation bias, pseudodiagnostic research uses exercises based on Bayes’ theorem to show that people’s information search patterns tend towards selecting diagnostically worthless data. This conclusion depends on the assertion that the calculation of a Bayes’ factor re-

lies upon data pair selection, with any other datum choice, therefore, being illogical. This view has been challenged by Crupi et al. (2009). In their theoretical note, Crupi et al. question whether the selection of non-paired data does lead to a situation in which Bayes' theorem cannot be applied. Arguing that if estimated values for missing data are used, they demonstrate that there may be an expected gain in epistemic utility associated with the selection of non-paired data which is greater than that associated with the selection of paired data. In particular, Crupi et al. claim that when choosing among hypotheses, the rational truth seeker will simply select "the most probable one" (Crupi et al., 2009, p. 974), with the expected utility gain being equal to the difference between the probability of a given hypothesis prior to the selection of further data and its expected probability once that data has been revealed.

However, a sensitivity of search patterns to contextual and information framing has also been found by both Mynatt et al. (1993) and Feeney et al. (2008). Mynatt et al. investigated the effect of task framing on search patterns by requiring their participants to complete either "action" or "inference" tasks. Here an "inference" task was taken to follow the standard pseudodiagnostic paradigm of deciding, for instance, the origins of an archaeological find. In contrast, the "action" tasks required the participants to decide on a course of action, such as which model of car to buy. The results suggest that when asked to infer a conclusion participants would fall prey to confirmation bias which did not occur with "action" tasks. Equally, Feeney et al. considered the effect of rarity on information selection choice. Asking their participants to decide which of three extra pieces of information was the most useful, they found that the presence of unusual, or rare, information led to an increase in diagnostic behaviour. In their first experiment, the presence of information regarding the number of houses with a swimming pool (the "rare" condition) rather than the number of houses with a garden (the "common" condition) showed an increase in the selection of the diagnostic information. These results were, however, questioned by D'addario and Macchi (2012) who suggest that the importance of information rarity has been overstated. Rather, D'addario and Macchi found that it was the subjective appraisal of the relative informative values of diagnostic criteria which was important. This view is broadly consistent with the Rational Categorisation

Model (Anderson, 1990, 1991) which suggests that known data are used to infer the unknown, thereby introducing the affect of prior knowledge and belief into the decision-making process (see, e.g., Sanborn et al., 2006).

There is, however, research which suggests that people are able to select diagnostically useful information. Over three experiments Trope and Bassok (1983) investigated the factors which influence the questions people might ask when hypothesis testing. In their first experiment Trope and Bassok allowed their participants to ask any questions they wished to help them determine whether an interviewee was polite or impolite. A variation of this task was used for the second experiment in which the participants chose from a predetermined list of twenty-four questions to decide whether an interviewee was introvert or extrovert. In both cases, the participants chose to ask questions which did not test the given hypothesis about their interviewee. In the third experiment, the participants were asked to rate the usefulness of the questions used in experiment two. Here the results showed a parallel between the question ratings and their use during the second experiment. From this Trope and Bassok concluded that there was “unequivocal support for the diagnostic strategy in social information gathering” (Trope and Bassok, 1983, p. 572). These were similar findings to the Trope and Bassok (1982) research which found a preference for improbable data selection.

According to Nelson et al. (2010), there are four statistical theories which are consistent with known data on information acquisition and they contrast experimental results for these models of information gain, Kullback-Leibler distance, probability gain and impact. Within the Bayesian reasoning framework, information gain and the Kullback-Leibler distance are essentially interchangeable (Nelson et al., 2010). Information gain, which has been proposed as a model of information search patterns for the Wason card selection task by Oaksford and Chater (1994), suggests that people should select data which results in the greatest reduction of uncertainty. Equally, the Kullback-Leibler distance (Kullback and Leibler, 1951; Kullback, 1959) provides a way to measure the difference between the pre- and post-data selection probability distributions. Since both approaches rely upon the Shannon (1948)

equation for the calculation of entropy, their results within this context are identical Oaksford and Chater (1996). As an example of their use, in the Wason selection task participants are presented with four cards (e.g., "A", "K", "2", and "5"), of which they may then select two in order to either support, or refute, a given rule, such as If there is a vowel on one side, then there must be an even number on the other. The logical choice, in this example, is for the participants to select the cards "A" and "5" since only these two cards can directly refute the hypotheses. However, according to Johnson-Laird and Wason (1970) most participants will select the cards "A" and "2". Oaksford and Chater (1994) argue that the selection of these cards is the result of a Bayesian decision to maximise information gain. Specifically, the amount of information gain is given as the summation of the expected information values of the conditions given on the other side of the card, which is equivalent to the Kullback-Leibler distance. Thus, for Oaksford and Chater (1994) the rational participant will choose the card which gives the greatest increase in information. Applied to the pseudodiagnosticity paradigm, the Oaksford and Chater (1994) "information gain" strategy would suggest that data selection should be entropy driven (Shannon, 1948) with the sole aim of maximally reducing systemic uncertainty. This is inconsistent with the Doherty et al. view as to the normativity of paired data selection, and the descriptive emphasis placed by Gigerenzer and Hoffrage (1995), and Gigerenzer and Goldstein (1996), on the importance of heuristics within decision-making.

Nelson et al. cite Baron (1985) as defining probability gain as a measure of "the extent to which [a datum] increases the probability of correctly guessing the category of a randomly selected item" (Nelson et al., 2010, p. 961). With equal base rate information, this is equivalent to the impact model (Klayman and Ha, 1987; Nelson et al., 2010) and simply means that the usefulness of data selection may be defined by the degree to which it causes a change of belief. In their first two experiments Nelson et al. found a participant preference for the probability gain model. In the first experiment participants were asked to classify species of plankton on the basis of two features. In the first part of the experiment, the "learning phase", the participants were shown pictures in which both differentiating characteristics were available and given feedback on their decision after each choice. During the

“information-acquisition” phase the participants could select information regarding only one characteristic of each plankton, with the likelihoods in each condition being manipulated to create disagreement about the utility of each feature. This was followed by a questionnaire which the participants were asked to rate which features of aliens would be the most useful for categorization, with probabilities being duplicated from the previous sections. The results indicated that during the information-acquisition phase, the higher probability feature was viewed 99% of the time. However, the results of the alien-categorization task were insignificant suggesting that personal experience may be important in information-acquisition tasks with purely statistical exercises not accurately reflecting human behaviour (Nelson et al., 2010). The third Nelson et al. experiment investigated the robustness of this preference for probability gain based information selection. Repeating the structure of experiment one, Nelson et al. created three conditions to manipulate the probability gain associated with the diagnostic features. The results showed a correlation between the manipulated probability gain and participant information choices.

The findings of the third experiment by Trope and Bassok (1983), which showed the participants’ ability to assess the diagnostic usefulness of different questions, have been widely replicated. Slowiaczek et al. (1992), van Wallendael and Hastie (1990) and Kareev and Halberstadt (1993) have all reached similar research conclusions. Clearly there is an issue of consistency with the pseudodiagnostic findings discussed above. Ignoring, for the moment, the fickle nature of participants, the research by Trope and Bassok and others came from the perspective of Social Psychology. As such these findings may arise, in part, from participant familiarity with the experimental scenarios. This would have an obvious parallel to the Mynatt et al. findings regarding the occurrence of diagnostic behaviour with subjective, as opposed to objective, tasks. This view would certainly tie in with that of Gigerenzer and Hoffrage (1995) who suggest that cognitive algorithms cannot be separated from the way in which they are presented. In this particular case, Gigerenzer and Hoffrage (1995) argue that the use of frequency formats, as opposed to the use of probabilities, will elicit a diagnostic response within the standard pseudodiagnostic paradigm. In their first experiment they found that 46%-50% of participants chose

diagnostically useful information when presented with frequency data, as opposed to only 16%-28% when given relative frequencies. Given that there is no mathematical reason for this difference, it would seem unreasonable to conclude anything other than that task familiarity is of great importance in participant behaviour.

There are two possibilities not examined by Nelson et al.. The first is put forward by Cheeseman and Stutz (2004) which is based on Maximum Entropy (“MaxEnt”) inference. In this theoretical paper, Cheeseman and Stutz define MaxEnt as “a method for using constraint information to find a set of point probability values... that assumes the least [Shannon] information consistent with the given constraints” (Cheeseman and Stutz, 2004, p.455). This is similar to the Jaynes (1957) definition of MaxEnt as the “least biased estimate possible on the given information; i.e., it is maximally non-committal with regard to missing information” (Jaynes, 1957, p.620). Cheeseman and Stutz argue that MaxEnt inference is similar to Bayesian inference but will produce different results since MaxEnt makes stronger assumptions than Bayes’ theorem about the absolute independence of known dependencies. They also point out that MaxEnt inference is not incremental in the same way manner as Bayes’ theorem, since the discovery of new information invalidates previous calculations rather than simply allowing for the updating of priors. However, since in the pseudodiagnosticity paradigm the existence of all relevant information, if not the actual information itself, is known to the participants, the importance of this is somewhat moot. The second possibility is, simply, that the structure of the pseudodiagnosticity paradigm and its use of ordinal decisions, as opposed to requiring estimates of likelihood, allows for alternative decision-making strategies to be used.

Chapters 3 and 4 consider the limitations of the naïve Bayes’ classifier as an approach for the calculation of probability. It is argued that these limitations raise questions about the validity of the naïve Bayes’ classifier both for the estimation of likelihood when the conditional independence of data cannot be guaranteed and, hence, as a model for human cognition. Instead, Chapter 3 develops a new expression, derived from quantum mechanics, which generates largely assumption free

estimates of probability. The value of this Quantum Bayes' conjecture as a model for participant estimations of likelihood is tested in Chapter 4.

Chapter 2

On the diagnostic value of relational information

2.1 Introduction

Psychology’s interest in decision-making stems from observed differences between the mathematical demands of data evaluation and human behaviour. Central to this idea is the premise that statistical frameworks, such as the naïve Bayes’ classifier (see, e.g., Oaksford and Chater, 2007), give normative accounts for interpreting probabilistic information that highlight the failings of human judgement. This paradigm has led to contrasting claims: while there are researchers who argue that people “violate principles of rational decision-making” (Slovic et al., 1976), others suggest that heuristic cognition satisfies most day-to-day decision-making needs (Simon, 1956). However, decision-making is a product of uncertainty. With absolute certainty, the decision to do, or do not, has predetermined consequences that define a rational course of action. It is only the risk associated with the unknown that demands cognitive resources to analyse available data and to assess the likely impact of every decision. Within this framework it becomes necessary to treat decision-making as a branch of probability theory, forcing researchers to adopt one of two opposite approaches in which they must either show that the human assessment of uncertainty fails to meet the normative standards of statistical best practice or offer credible replacement narratives derived from behavioural descriptors.

There is an inherent danger which arises from this schism between the normative and descriptive accounts of decision-making. While the consonance and dissonance of these models might give insight into the limits and errors of human cognition, any conclusions drawn rely upon the integrity of the underlying theory and approach. Not only may unwarranted assumptions find problems where none exist, but they can further confound research by becoming an unintended part of the problem itself (Žižek, 2011). For instance, an unjustified presumption of a causal relationship between the procedural rules of specific statistical techniques and expected participant behaviour may cause other experimental interpretations to go ignored. Illustrating this problem are the contrasting approaches of two earlier papers on patterns of information search. Where Oaksford and Chater (1994, 1995) used a descriptive account of observations from the Wason selection task (Wason, 1968) to develop a diagnostic relevance-based “information gain” strategy, Doherty et al. (1979) relied upon a strict, normative interpretation of Bayesian analysis to conclude that data selections show dysfunctional cognitive tendencies. It was this tendency that Doherty et al. termed “pseudodiagnosticity”, arguing that their participants selected data which were believed to be diagnostically useful, but which were actually useless within a Bayesian framework since data “pairs” were not formed and, hence, strict Bayesian ratios could not be calculated.

Within the field of Bayesian rationality the dogmatically objectivist view of Doherty et al. is unusual. Bayesian theory allows for the subjective allocation of posterior distributions to aid the inference of unknown data. While the Doherty et al. approach may lead to a consistent calculation of likelihood, computational analysis (presented in 2.3) demonstrates that this is sub-optimal, in comparison to a subjective, epistemologically driven data selection strategy, when making categorical decisions.

This chapter presents a novel theory of “relational information” which emphasises the derivation of knowledge from the relationships between ordinal data. In this, Relational Information Theory posits that information search is guided by a holistic view of probabilistic systems, with the paramount objective, prior to a decision being

made, being to establish numerical representations of the conditionalised relationships that exist between data. While this idea is consistent with standard Bayesian theory, in that the motivation behind data selection is to constrain the subjective element of the unknown posterior distributions, Relational Information Theory also contrasts sharply with the paradigmatic view that data search is guided by the need to compare competing hypotheses. By removing analytical assumptions, such as decision-making being based on competing choices, and the conditional independence of data in the naïve Bayes classifier, Relational Information Theory offers a new approach not previously considered by academic literature that bridges the gap between normative and descriptive decision-making theory. This assertion is supported by computational modelling, theory, and empirical work. Indeed, by investigating whether people can interpret probabilities to make reasonable decisions, how their understanding of a problem guides data choice, and why observed behaviour might be at odds with the needs of a strict Bayesian analysis, Relational Information Theory not only calls into doubt the claims Doherty et al., but also helps bridge the Oaksford and Chater “information gain” and Johnson-Laird (1983) “mental model” perspectives.

2.2 The case of pseudodiagnosticity

Any uncertainty associated with decision-making can stem only from either imperfect knowledge of relevant data or the consequences of available decision choices. Given that the relative desirability and likelihood of different decision outcomes may be subjective, research paradigms often concentrate on consequence-free scenarios with the analytic emphasis placed on knowledge acquisition strategies. Examples of this style of experiment include those premised on hypothesis nullification where it is logical to choose data that can negate, instead of support, an established proposition, e.g., the Wason selection task Wason (1968), and diagnostic decision-making Doherty et al. (1979).

In a two-part experiment, Doherty et al. asked students to investigate the ori-

gins of an archaeological find. Given a list of eight individuating characteristics, and told that the discovery could have come from either of two islands, the first exercise provided the participants with the base-rates of earlier finds, along with a posterior information matrix comprising the percentage data for two of the individuating characteristics. Except for one piece of “anchor” information, removable stickers concealed the figures. The instructions allowed for the removal of one sticker to show an extra piece of information before requesting a decision on the find’s most likely origin. The second part of the experiment presented the information for the remaining characteristics, with the participants allowed to remove a further six of the twelve stickers while updating their decision with each new piece of information.

Doherty et al. expected their participants’ behaviour to be consistent with a normative description of Bayes’ theorem that requires the selection of data “pairs” to allow the consistent calculation of Bayesian odd ratios. Thus, in the first section of the experiment with the anchor information provided, Doherty et al. predicted that their participants would choose to complete data pairs by selecting the datum in the nullifying hypothesis for the same characteristic as the anchor information. However, their results showed that only around 20% of the participants chose the data pair, while just 19 from 152 participants selected three data pairs in the second section. It was this that Doherty et al. termed “pseudodiagnosticity,” positing that while participants thought they were behaving in a rational and diagnostic way, the lack of data pairs meant that their choices were worthless and illogical. Mynatt et al. (1993) have since both confirmed this general pattern of information search and provided a more detailed analysis of the first experimental stage, finding that while 28% of participants selected the data pair, 59% selected the datum from the same column as the anchor information, and 13% selected the diagonal cell. These selection patterns are, however, sensitive to question framing with Feeney et al. (2008) showing that including “rare”, or unusual, information increases the likelihood of data pair selection.

2.3 An epistemological interpretation

The claims of Doherty et al. rely on their interpretation of Bayes' theorem. Often presented as (2.1), Bayes' theorem calculates the likelihood of any hypothesis, A_j , being true given both its prior distribution in relation to the other hypotheses, $P(A_j)$, and the conditional probability of its posterior data, $P(B|A_j)$ (see, e.g., Ramachandran and Tsokos, 2009).

$$P(A_j|B) = \frac{P(B|A_j)P(A_j)}{\sum_{i=1}^n P(B|A_i)P(A_i)} \quad (2.1)$$

To exemplify, given the example contingency data in Figure 2.1 it is trivial to calculate that any chosen house with both a blue front door, D_1 , and a garage, D_2 , is most likely to be on Street A with a probability of around 0.58 (2.2).

	Street A (H_1)	Street B (H_2)
Number of houses	10	10
% with a blue door (D_1)	0.8	0.7
% with a garage (D_2)	0.6	0.5

Figure 2.1: Example contingency table data for the occurrence of houses with blue doors, or garages, on two streets.

$$P(H_1|D_1, D_2) = \frac{0.5 \times 0.8 \times 0.6}{(0.5 \times 0.8 \times 0.6) + (0.5 \times 0.7 \times 0.5)} \approx 0.578, \quad (2.2)$$

where $P(H_i) = 10/(10 + 10) = 0.5$ for both $i = 1, 2$.

With incomplete information, see Figure 2.2, Doherty et al. argue that it is correct to select α , the paired datum to the “anchor” information given in $P(D_1|H_1)$. It is only this strategy that makes it possible to calculate a Bayesian likelihood ratio independent of any assumptions about missing data, other than that all unknowns should take the same value.

	Street A (H_1)	Street B (H_2)
Number of houses	10	10
% with a blue door (D_1)	0.8	α
% with a garage (D_2)	β	δ

Figure 2.2: Example “pseudodiagnosticity” contingency table, derived from Figure 2.1, where α , β , and δ represent unknown data. The “anchor” information, $P(D_1|H_1)$, is provided.

Crupi et al. (2009) have challenged the orthodoxy of this view. Arguing that estimations for unknown data, made using a principle of indifference, explain selection patterns, they further propose that the selection of a non-paired datum may also be the most efficient strategy. The Crupi et al. most “indifferent” estimator is the least biasing figure which, given a presumed standard distribution for each of the probability density functions, they argue is the median of each datum’s possible value range. The assignation of such “indifferent” estimated values to the α , β , and δ terms allows the guiding of data selection through expected epistemic utility gain values. Extending their argument, Crupi et al. also show that selecting the diagonal datum, δ , instead of the paired term, α , has a neutral effect on the error of any calculated likelihood ratio. Table 2.1 supports this claim, showing that the accuracy rates of the calculated Bayesian ratios using the α and δ terms are identical. The code used to generate Tables 2.1 and 2.2 is presented in Appendices A.1 and A.2.

Beyond the inherent reasonableness underpinning the notion that people will estimate unknown data values, a mathematical justification for the Crupi et al. view is provided by the de Finetti theorem of exchangeable probabilities (Diaconis and Freedman, 1980). As presented in (Caves et al., 2002b, pp. 8–9), the de Finetti theorem defines “belief” as a second-order probability of probabilities values, $P(p)$, for any unknown, but real, exchangeable probability density function, p , and is directly equivalent to the Crupi et al. measure of greatest “indifference”.

The de Finetti theorem relies upon two propositions: first, an underlying assumption of Bayes’ theorem that the posterior data are conditionally independent of each other, but have a non-trivial dependence on the prior distribution, and;

second, the weaker statistical assumption that there is an identical and independent symmetrical distribution across all probability density functions (Ramachandran and Tsokos, 2009; de Finetti, 1974; Hewitt and Savage, 1955; Diaconis and Freedman, 1980). It is this second assumption which allows for infinite exchangeability in the de Finetti theorem, and without which estimations of unknown values would be meaningless.

Any probability distribution is symmetric and, therefore, exchangeable if there is no variation under different permutations, i.e., that

$$p(x_{\alpha(1)}, x_{\alpha(2)}, \dots x_{\alpha(n)}) = p(x_1, x_2, \dots x_n) \quad (2.3)$$

for any permutation $\alpha \in \{1, 2, \dots n\}$ (Caves et al., 2002b). From this it follows not only that the binary “has or hasn’t” probability distributions for each given feature in Figure 2.2 are exchangeable, but that the same also applies to the compound, bivariate, binary-option probability distribution $\alpha \cap \delta$. Thus, the Crupi et al. measure of indifference may be taken as the best epistemological estimate of likelihood for any probability density function where there is no knowledge of the function itself.

The difference between the views of Doherty et al. and Crupi et al. reflects the division between the objective and subjective views of Bayesian probability, either emphasising the derivation of probability from knowledge alone or allowing for the influence of belief. Fortunately, the constraints of the 2×2 contingency table, in the pseudodiagnosticity paradigm, provide a tractable analytical framework with which to compare the effectiveness of the two approaches. Here, computational modelling of all possible combinations for a 2×2 contingency table reveals that while the Crupi et al. strategy is generally the more helpful for making correct decisions, it is data pair selection which provides the best estimations of the Bayes’ likelihood ratio (Tables 2.1 and 2.2). Thus, there is an unidentified tension between the general need to make a valid categorical decision and the need to calculate a reasonable estimation of likelihood – an issue highlighted by Doherty et al.’s use of a two-alternative forced-choice format given that their research analysis focused on estimations of probability.

Priors $P(H_1):P(H_2)$	# Trials	α selected		δ selected		β selected		Selection strategy			
								Av. Bayes' ratio		Av. α estimate	
		Nearest	%	Nearest	%	Nearest	%	Same	$P(H_1 D_1, D_2):P(H_2 D_1, D_2)$	$P(H_1 D_1, D_2):P(H_2 D_1, D_2)$	Av. Crupi estimate*
10:90	810000	427612	53.0%	427612	53.0%	379681	47.0%	2707	0.2124 : 0.7876	0.1611 : 0.8389	0.1611 : 0.8389
20:80	2560000	1331195	52.2%	1331195	52.2%	1220755	47.8%	8050	0.3001 : 0.6999	0.2593 : 0.7407	0.2593 : 0.7407
30:70	4410000	2296876	52.1%	2296876	52.1%	2107856	47.9%	5268	0.3724 : 0.6276	0.3445 : 0.6555	0.3445 : 0.6555
40:60	5760000	3001148	52.3%	3001148	52.3%	2739543	47.7%	19309	0.4377 : 0.5623	0.4235 : 0.5765	0.4024 : 0.5976
50:50	6250000	3275309	52.4%	3275309	52.4%	2972131	47.6%	2560	0.5000 : 0.5000	0.5000 : 0.5000	0.4579 : 0.5421
60:40	5760000	3020419	52.6%	3020419	52.6%	2724391	47.4%	15190	0.5623 : 0.4377	0.5765 : 0.4235	0.5216 : 0.4784
70:30	4410000	2320537	52.7%	2320537	52.7%	2084231	47.3%	5232	0.6276 : 0.3724	0.6555 : 0.3445	0.5942 : 0.4058
80:20	2560000	1346418	52.8%	1346418	52.8%	1205503	47.2%	8079	0.6999 : 0.3001	0.7407 : 0.2593	0.6796 : 0.3204
90:10	810000	419424	51.9%	419424	51.9%	388345	48.1%	2231	0.7876 : 0.2124	0.8389 : 0.1611	0.7894 : 0.2106
33330000		17438938	52.4%	17438938	52.4%	15822436	47.6%	68626	0.5000 : 0.5000	0.5000 : 0.5000	0.4678 : 0.5322

Table 2.1: Comparison of the effectiveness of the Crupi et al. (2009) and Doherty et al. (1979) selection strategies for accuracy of Bayes' ratio estimation.

Note: *The Crupi et al. strategy percentages are based on the number of occasions in which there was a difference between the expected values of $P(H_1|D_1, D_2)$ and $P(H_2|D_1, D_2)$.

Priors $P(H_1):P(H_2)$	# Trials	Selection strategy					
		α selected		δ selected		β selected	
		Correct	%	Correct	%	Correct	%
						Crupi strategy	Crupi strategy
						Correct	%*
10:90	810000	726786	89.7%	726786	89.7%	706793	87.3%
20:80	2560000	2150018	84.0%	2150018	84.0%	1997181	78.0%
30:70	4410000	3494897	79.2%	3494897	79.2%	3206190	72.7%
40:60	5760000	4355968	75.6%	4355968	75.6%	4140276	71.9%
50:50	6250000	4622650	74.0%	4622650	74.0%	4638956	74.2%
60:40	5760000	4355968	75.6%	4355968	75.6%	4486966	77.9%
70:30	4410000	3494897	79.2%	3494897	79.2%	3638640	82.5%
80:20	2560000	2150018	84.0%	2150018	84.0%	2235001	87.3%
90:10	810000	726786	89.7%	726786	89.7%	750580	92.7%
	33330000	26077988	78.2%	26077988	78.2%	25800583	77.4%
						26490269	80.6%

Table 2.2: Comparison of the effectiveness of the Crupi et al. (2009) and Doherty et al. (1979) selection strategies for categorical decisions.

Note: The *Crupi et al. strategy percentages are based on the number of occasions in which there was a difference between the expected values of $P(H_1|D_1, D_2)$ and $P(H_2|D_1, D_2)$.

2.4 An information theoretic interpretation

Although the arguments of Crupi et al. appear compelling, they do not generalise. In particular, extending the experimental paradigm to provide lower value bounds for alpha, beta, or delta, would change their indifference values. For instance, a lower bound of 0.5 for any datum would give an estimated epistemological value of 0.75 and increase its selection likelihood. Given that there may be a greater, albeit imprecise, knowledge of this datum than others, such a selection strategy would be surprising.

Information theory provides a theoretical counterpoint to the epistemological approach of Crupi et al.. Although counter-intuitive, the amount of information in a system is equivalent to its entropy, or level of disorder (Shannon, 1948). Thus, using (2.4) to calculate an entropy value, $H(X)$ provides a measure of the degree to which a system can “surprise” (Ben-Naim, 2012). Since attempts to predict the outcome of a random measurement are futile, any information theoretic selection strategy cannot aim to maximise knowledge gain, but only to reduce systemic entropy with knowledge acquisition being the consequential result. The merit of this approach lies in it distinguishing between the knowledge held by a decision-maker and the information within the system, with a broad inverse relationship existing between the two.

$$H(X) = - \sum_{i=1}^n p(x_i) \log_2 p(x_i) \quad (2.4)$$

It is this approach which Oaksford and Chater (1994, 1995) adopted to explain observable selection patterns in the Wason selection task. In their “information gain” model they argue that it is the greatest reduction in system uncertainty, calculated across the expected effect of all possible results, which should guide data choice. For the pseudodiagnosticity case of two competing, even-chance hypotheses, selecting a datum from the hypothesis with the highest absolute level of entropy is, a priori, most likely to give the greatest reduction in uncertainty. With non-even priors, it is enough to scale calculated entropy by the priors. Thus, it is the largest of (2.5) which guides hypothesis selection, with the particular choice of any datum

being irrelevant under the de Finetti theorem.

$$H(H_j) = P(H_j) \left\{ - \sum_{i=1}^n p(x_i|H_j) \log_2 p(x_i|H_j) \right\}; j = 1, 2. \quad (2.5)$$

With no prior knowledge of the unknown data, rather than taking the epistemological approach of Crupi et al., information theory assumes that a maximum entropy, “MaxEnt”, distribution applies since this introduces the least extra information into the decision-making system. Often represented by a maximally non-committal standard frequency distribution (Park and Bera, 2009), a MaxEnt probability density function would imply an estimated value of 0.5 for all unknown values in the contingency table (Figure 2.2). However, since the effects of the unknown data β and δ are the same for their respective hypotheses, they cancel for entropy calculation and comparison. This cancellation means that for Hypothesis 1 in Figure 2 the unknown probability density function, generated from the prior datum $P(H1)$ of 10 and the anchor information $P(D1|H1)$, comprises eight equal-likelihood elements which give an entropy value $H(H1)$ of 1.5 bits (2.6). With an assumed value of 0.5 for α , the unknown probability density function for hypothesis 2 comprises five equal-likelihood elements which give an entropy value $H(H2)$ of 1.16 bits (2.7).

$$\begin{aligned} H(H_1) &= \frac{1}{2} \times \left\{ - \left(\frac{1}{8} \times \log_2 \frac{1}{8} \right) \times 8 \right\} \\ &= \frac{1}{2} \times - \{ - \log_2 (8) \} \\ &= \frac{1}{2} \times \log_2 (8) \\ &= \frac{1}{2} \times 3 \\ &= 1.5 \text{ bits} \end{aligned} \quad (2.6)$$

$$\begin{aligned}
H(H_2) &= \frac{1}{2} \times \left\{ - \left(\frac{1}{5} \times \log_2 \frac{1}{5} \right) \times 5 \right\} \\
&= \frac{1}{2} \times - \{ - \log_2 (5) \} \\
&= \frac{1}{2} \times \log_2 (5) \\
&\approx \frac{1}{2} \times 2.322 \\
&\approx 1.16 \text{ bits}
\end{aligned} \tag{2.7}$$

Since, for comparison, using \log_2 cancels, an information-theory based selection strategy becomes the simple heuristic of choosing from the hypothesis that possesses the highest expected level of information, i.e., whichever has the greatest likely range of values.

Extending the pseudodiagnosticity paradigm to provide extra non-specific information, such as a lower boundary, generates the same expected value for α as an epistemological approach. For instance, using Figure 2.2, a lower bound of 5 for the number of houses on Street B with a blue door gives an estimated α value of 0.75. However, fixing the values for five elements in the probability density function means they form no part of the entropy calculation which now only considers the remaining, hypothetical, 2.5 homes. This probability density function generates an information value of 0.66 bits (2.8) showing that knowledge of the lower boundary should reduce interest in the associated hypothesis rather than increase it. The effect of a lower bound for $H_2|D_1$ on the prediction success rate for ordinal decisions is shown in Table 2.3, where the overall success of an epistemological approach is 81.4% compared to a success rate of 83.4% for an Information Theory approach. The code used to generate Table 3 is available in Appendix A.3.

$$\begin{aligned}
H(H_2) &= \frac{1}{2} \times \left\{ - \left(\frac{2}{5} \times \log_2 \frac{2}{5} \right) \times 2.5 \right\} \\
&= \frac{1}{2} \times - \left\{ - \log_2 \left(\frac{5}{2} \right) \right\} \\
&= \frac{1}{2} \times \log_2 (2.5) \\
&\approx \frac{1}{2} \times 1.322 \\
&\approx 0.66 \text{ bits}
\end{aligned} \tag{2.8}$$

2.5 A relational information theoretic interpretation

Insofar as it is justifiable to presume that statistics have both meaning and inherent value, statistics can only describe and quantify the relationships that may exist between individual data points, as well as how groups of data relate to other real or imaginary sets. A datum itself has no statistical worth unless contextualised by other data. However, any theoretical or mathematical assumptions or simplifications that underpin a statistical method may confound and obfuscate research findings if applied beyond the minimum scope required for analytical purposes. This is as true of Bayes' theorem as any other method. With no incontrovertible demonstration of assumptive and presumptive confluence, the use of any approach is only justifiable through the belief that either it is the best, albeit flawed, tool available, or that no biasing affect or effect arises from assumption noncompliance.

As used by Doherty et al., Bayes' theorem relies on two assumptions. First, as mentioned above, the posterior data must be conditionally independent of each other while having non-trivial dependencies on the prior distribution and, second, the competing hypotheses must be both exhaustive and conditionally independent of each other. The reasoning behind these assumptions is simple: the data must, a priori, be a part of its allotted hypothesis; the conditional independence of the data allows, through the multiplication of marginal probabilities, its concatenation into

Priors $P(H_1):P(H_2)$	# combinations	Selection strategy							
		α selected		δ selected		β selected		Crupi strategy*	
		Correct	%	Correct	%	Correct	%	Correct	%
10:90	414000	396846	95.9%	403968	97.6%	396846	95.9%	396846	95.9%
20:80	1312000	1194109	91.0%	1246679	95.0%	1194109	91.0%	1194109	91.0%
30:70	2268000	1922995	84.8%	2080134	91.8%	1925488	84.9%	1922995	84.8%
40:60	2976000	2278864	76.6%	2599410	87.3%	2381521	80.0%	2278864	76.7%
50:50	3250000	2283304	70.3%	2673483	82.3%	2570494	79.1%	2450981	75.4%
60:40	3024000	2117011	70.0%	2378625	78.7%	2442015	80.8%	2335078	78.5%
70:30	2352000	1728660	73.5%	1859196	79.0%	1977688	84.1%	1938093	82.4%
80:20	1408000	1115355	79.2%	1859196	79.0%	1239119	88.0%	1213393	87.3%
90:10	486000	422221	86.9%	429303	88.3%	451696	92.9%	448922	92.4%
	17490000	13459365	77.0%	14831548	84.8%	14578976	83.4%	14179281	81.4%
								14406260	83.4%

Table 2.3: Success rate for the Crupi et al. strategy against an Information Theory and other search strategies in selecting H_1 or H_2 compared to the Bayes' factor for a diagnostic matrix with two hypotheses and two diagnostic criteria when $D_1|H_2$ has a known minimum value of 50% of the base-rate.

Notes: *The percentages given for the Crupi et al. strategy are based on the number of occasions in which there was a difference between the expected values of $P(H_1|D_1, D_2)$ and $P(H_2|D_1, D_2)$. **The percentages given for the Information Theory strategy are based on the number of occasions in which there was a difference between the calculated entropy values of $P(H_1|D_1, D_2)$ and $P(H_2|D_1, D_2)$.

a single representation of the hypothesis; and the hypotheses must be conditionally independent since the need to calculate an odds ratio demands they oppose each other. Thus, the expression (2.1) merely generates a unified representation of contingency data to calculate the simplest version of a likelihood ratio, i.e., (2.9).

$$P(H_1|D_1, D_2...D_n) = \frac{P(D_1, D_2...D_n|H_1)}{P(D_1, D_2...D_n|H_1) + P(D_1, D_2...D_n|\overline{H_1})} , \quad (2.9)$$

where $P(H_1) + P(\overline{H_1}) = 1$.

Given the underlying assumption in Bayes' theorem of conditionally independent posterior data, it is possible that a contingency table representation derived from the multiplication of marginal probabilities will be non-isomorphic, i.e., that the representation will not be an equivalent mathematical model which encodes all internal information structures. This is important since although there may be no reason to assume the conditional dependence of data, there is also no reason to dismiss the possibility. For instance, the residents of the example houses in Figure 2.1 might be more likely to favour a blue front door if they also have a tree in the garden. Alternatively, the opposite might be true with an aversive relationship existing between door colour and tree planting. As a consequence, it is the approach which can create the closest approximation of not only the contingency data but also any relationships between them which must, de facto, be normative.

All that is certain is that the information given in Figure 2.1 does not have to be mutually exclusive, and that the Bayes' theorem assumptions define contextual relationships between the data. Indeed, while individual datum may or may not possess statistical independence Bayes' theorem establishes relationships through their mutual dependence on a common hypothesis and its prior distribution. Equally, the requirement that $P(H_1) + P(\overline{H_1}) = 1$ specifies a relationship between the competing hypotheses. Thus, there is a mathematical homogeneity to contingency tables, such as Figure 2.1, which allows knowledge of even independent data to provide knowledge of others in a way that enriches understanding of how all the data in a contingency table works as a complete and integrated statistical system. The exem-

plification of this homogeneity is the range of possible intersection values between D_1 and D_2 for each hypothesis which mean it is (2.10) that gives the correct likelihood ratio calculation, rather than the naïve Bayes' expression (2.1). Hence, the only absolute truth to derive from Figure 2.1 is that $P(H_1|D_1 \cap D_2)$ must lie in the range of 0.44–0.75 (2.11). The ranges for $P(D_1 \cap D_2|H_i)$ are generated from the minimum and maximum frequencies, calculated using (2.12), and given in (2.13).

$$P(H_1|D_1 \cap D_2) = \frac{P(H_1)P(D_1 \cap D_2|H_1)}{P(H_1)P(D_1 \cap D_2|H_1) + P(H_2)P(D_1 \cap D_2|H_2)} \quad (2.10)$$

$$\begin{aligned} P(H_1|H_2 + 1) &= \frac{\min(D_1 \cap D_2|H_1)}{\min(D_1 \cap D_2|H_1) + \max(D_1 \cap D_2|H_2 + 1)} \\ &\dots \\ &\frac{\max(D_1 \cap D_2|H_1)}{\max(D_1 \cap D_2|H_1) + \min(D_1 \cap D_2|H_2 + 1)} \\ &= \left\{ \frac{4}{4+5}, \dots, \frac{6}{6+2} \right\} \\ &\approx \{0.444, \dots, 0.75\} \end{aligned} \quad (2.11)$$

$$\begin{aligned} n(D_1 \cap D_2|H_i) &\in \\ &\left\{ \begin{aligned} &\left[n(D_1|H_i) + n(D_2|H_i) - n(H_i), \dots, \min(n(D_1|H_i), n(D_2|H_i)) \right] \\ &\quad \text{if } n(D_1|H_i) + n(D_2|H_i) > n(H_i) , \\ &\text{or} \\ &\left[0, \dots, \min(n(D_1|H_i), n(D_2|H_i)) \right] \\ &\quad \text{if } n(D_1|H_i) + n(D_2|H_i) \leq n(H_i) . \end{aligned} \right. \end{aligned} \quad (2.12)$$

These values for Figure 2.1 are

$$\begin{aligned} n(D_1 \cap D_2|H_1) &\in \{4, 5, 6\}, \\ n(D_1 \cap D_2|H_2) &\in \{2, 3, 4, 5\} . \end{aligned} \quad (2.13)$$

However, by describing the pseudodiagnosticity problem as (2.10), the intra-hypothesis relationships that exist between the data allow the derivation of all intersection values from just one, i.e., (2.14).

$$\begin{aligned}
D_1 \cap D_2 &= D_2 - (\overline{D_1} \cap D_2) \\
D_1 \cap \overline{D_2} &= D_1 - (D_1 \cap D_2) \\
\overline{D_1} \cap D_2 &= \overline{D_1} - (\overline{D_1} \cap \overline{D_2}) \\
\overline{D_1} \cap \overline{D_2} &= \overline{D_2} - (D_1 \cap \overline{D_2}) .
\end{aligned} \tag{2.14}$$

Applying (2.14) to the twelve possible combinations of $n(H_1|D_1 \cap D_2)$ and $n(H_2|D_1 \cap D_2)$ in (2.13), derived from (2.12), generates a full and exhaustive description of every possible real contingency table, and is presented in Figure 2.3.

The noticeable feature of Figure 2.3 is that to derive the odds ratio from anything other than the means of the frequency ranges for each hypothesis requires at least one intersection value to be zero. This distribution pattern occurs in all possible contingency tables, although where the mean value is a non-integer, e.g., $\mu\{n(H_2|D_1 \cap D_2)\}$ in Figure 2.1, the tables adjacent to the mean value both contain a complete set of non-zero intersections. With no information to suggest a conditional dependence bias, an odds ratio calculated from these mean figures produces a better estimate of the likelihood than the standard multiplication of marginal probabilities. For Figure 2.1 this equates to $P(H_1|D_1 \cap D_2) \approx 0.588$ (3.2) rather than the standard Bayesian calculation of approximately 0.578 (2.2).

$$\begin{aligned}
P(\mu[n(D_1 \cap D_2|H_1)]) &= \frac{1}{10} \times \frac{1}{3}(4 + 5 + 6) = 0.5 , \\
P(\mu[n(D_1 \cap D_2|H_2)]) &= \frac{1}{10} \times \frac{1}{4}(2 + 3 + 4 + 5) = 0.35 \\
\Rightarrow P(H_1 | \mu[D_1 \cap D_2]) &\approx 0.588
\end{aligned} \tag{2.15}$$

In this interpretation there are, therefore, two strategies available to the decision-

	H_1	H_2		H_1	H_2
$D_1 \cap D_2$	4	2	$D_1 \cap D_2$	4	3
$D_1 \cap \overline{D_2}$	4	5	$D_1 \cap \overline{D_2}$	4	4
$\overline{D_1} \cap D_2$	2	3	$\overline{D_1} \cap D_2$	2	2
$\overline{D_1} \cap \overline{D_2}$	0	0	$\overline{D_1} \cap \overline{D_2}$	0	1

	H_1	H_2		H_1	H_2
$D_1 \cap D_2$	4	4	$D_1 \cap D_2$	4	5
$D_1 \cap \overline{D_2}$	4	3	$D_1 \cap \overline{D_2}$	4	2
$\overline{D_1} \cap D_2$	2	1	$\overline{D_1} \cap D_2$	2	0
$\overline{D_1} \cap \overline{D_2}$	0	2	$\overline{D_1} \cap \overline{D_2}$	0	3

	H_1	H_2		H_1	H_2
$D_1 \cap D_2$	5	2	$D_1 \cap D_2$	5	3
$D_1 \cap \overline{D_2}$	3	5	$D_1 \cap \overline{D_2}$	3	4
$\overline{D_1} \cap D_2$	1	3	$\overline{D_1} \cap D_2$	1	2
$\overline{D_1} \cap \overline{D_2}$	1	0	$\overline{D_1} \cap \overline{D_2}$	1	1

	H_1	H_2		H_1	H_2
$D_1 \cap D_2$	5	4	$D_1 \cap D_2$	5	5
$D_1 \cap \overline{D_2}$	3	3	$D_1 \cap \overline{D_2}$	3	2
$\overline{D_1} \cap D_2$	1	1	$\overline{D_1} \cap D_2$	1	0
$\overline{D_1} \cap \overline{D_2}$	1	2	$\overline{D_1} \cap \overline{D_2}$	1	3

	H_1	H_2		H_1	H_2
$D_1 \cap D_2$	6	2	$D_1 \cap D_2$	6	3
$D_1 \cap \overline{D_2}$	2	5	$D_1 \cap \overline{D_2}$	2	4
$\overline{D_1} \cap D_2$	0	3	$\overline{D_1} \cap D_2$	0	2
$\overline{D_1} \cap \overline{D_2}$	2	0	$\overline{D_1} \cap \overline{D_2}$	2	1

	H_1	H_2		H_1	H_2
$D_1 \cap D_2$	6	4	$D_1 \cap D_2$	6	5
$D_1 \cap \overline{D_2}$	2	3	$D_1 \cap \overline{D_2}$	2	2
$\overline{D_1} \cap D_2$	0	1	$\overline{D_1} \cap D_2$	0	0
$\overline{D_1} \cap \overline{D_2}$	2	2	$\overline{D_1} \cap \overline{D_2}$	2	3

Figure 2.3: Every possible real contingency table that may be derived from Figure 2.1

maker where the aim of information search is either to increase knowledge in the pure information theoretic sense, or to constrain the estimated probability range by investigating the relationships between data through testing of the weakest information theoretic hypothesis for possible null intersections. That these different approaches exist might explain the lack of a clear selection strategy observed by Doherty et al. where a 2×2 contingency table only affords one degree of selection freedom and, hence, forces a choice between the competing search strategies. Where more degrees of freedom are available, for instance with a larger contingency table, there is experimental evidence of a “salami” selection strategy which follows the information theoretic interpretation up to the last selection, at which point the strategy reverses. This is entirely consistent with the principles of Relational Information Theory since identification of the weakest hypothesis, in information theoretic terms, is required to help constrain the estimated probability range, but this cannot be achieved until as much theoretically strong information as possible has been selected. This phenomenon is investigated in Experiments 3 and 4 (Research question 5).

Thus, a relational information theoretic approach to decision-making exists as part of the more general psychological theory of mental models (see Johnson-Laird, 1983). However, unlike Johnson-Laird (2010), who has argued that decisions arise from the comparison of competing mental models, here the establishing of relationships between data helps generate a rich, holistic understanding of probabilistic information as an integrated system. In this way the relational approach forms a cognitive totality which extends beyond the mere guiding of data selection to include the process of data assessment itself, with the decision emanating directly from the constructed model.

While a decision for the “street/house” exemplar in Figure 2.1 is seen to arise directly from Figure 2.3, the question asked is fundamentally different to that posed by Doherty et al. due to the existence of time (t) as a paradigmatic variable. Indeed, the “street/house” exemplar is a static, time-independent, question where the information in the contingency table exists independently of any decisions made and requires no updating of the contingency data following a decision. However, Doherty

et al. asked a question which required allocating an archaeological find to one of two possible origin islands. There is a fundamental mathematical difference between requiring the appraisal of data as is, at $t=0$, and projecting forward to a future state at $t=t+1$, or even $t=\infty$, where knowledge of either the system development function or the expected system state at infinity must affect any decision. Illustrating this problem with the $t=\infty$ case, an iterative Bayesian repetition of the exercise would require the updating of data following every decision. With no verification of the correctness of each allocation, this process may lead to the same decisions occurring with ever-increasing certainty. Figure 2.4 shows this effect by updating the data from Figure 2.1 twice, i.e., to $t=t+2$. Given that only the first contingency table is fact, with subsequent decisions being only conjecture, the increasing divergence of the updated table from the original would suggest that, under these circumstances, it is not only wrong to use Bayes' theorem as purely an inferential statistic, but that only the integrated approach of Relational Information Theory can bridge the analytical demands of both questions.

With no information to perform a regression analysis on the contingency table, it is not possible to extrapolate to a future state, which must, therefore, be taken to be a simple multiple of the original. For instance, after twenty iterations of Figure 2.1, the contingency table should develop into the isomorphic version of Figure 2.5.

This implicit linear development of the contingency table provides a non-standard variation to Bayesian decision-making derived from the comparison of the original table with the ones that would result from each possible decision. Such an approach is only possible by understanding how the information system works as whole, with the "correct" choice being the one that shows the least structural divergence from the original contingency table at $t=t+x$.

Figures 2.6-2.7 illustrate how Figure 2.1 would develop with the updating of data following each hypothesis' selection. The choice, therefore, between H_1 and

$$t=0, P(H_1|D_1,D_2) \approx 0.578$$

	H_1	H_2
Base-rate	10	10
$D_1\%$	0.8	0.7
$D_2\%$	0.6	0.5



$$t=t+1, P(H_1|D_1,D_2) \approx 0.599$$

	H_1	H_2
Base-rate	11	10
$D_1\%$	0.82	0.7
$D_2\%$	0.64	0.5



$$t=t+2, P(H_1|D_1,D_2) \approx 0.614$$

	H_1	H_2
Base-rate	12	10
$D_1\%$	0.83	0.7
$D_2\%$	0.67	0.5

Figure 2.4: The iterative effect of speculative Bayesian updating

$$t=t+20, P(H_1|D_1,D_2) \approx 0.578$$

	H_1	H_2
Base-rate	20	20
$D_1\%$	0.8	0.7
$D_2\%$	0.6	0.5

Figure 2.5: The expected contingency table after 20 updates

	H_1	H_2
Base-rate	11	10
$D_1\%$	0.82	0.7
$D_2\%$	0.64	0.5

Figure 2.6: The development of Figure 2.1 after the selection of H_1

H_2 becomes the straightforward comparison of the relative distance between the likelihood ratio ranges. Hence, if the probability range for Figure 2.6 is 0.5–0.777

	H_1	H_2
Base-rate	10	11
D_1 %	0.8	0.73
D_2 %	0.6	0.55

Figure 2.7: The development of Figure 2.1 after the selection of H_2

(2.16), and for Figure 2.7 is 0.4–0.666 (2.17), then given a target range from Figure 2.1 for $P(H_1)$ of 0.444–0.75 (2.11) the least divergent, and hence correct, choice is H_1 which exceeds the target by 0.07 as opposed to 0.044 for H_2 .

$$\begin{aligned}
P(H_1|D_1 + 1 \cap D_2 + 1) &= \\
&\frac{\min(D_1 + 1 \cap D_2 + 1|H_1)}{\min(D_1 + 1 \cap D_2 + 1|H_1) + \max(D_1 \cap D_2|H_2)} \\
&\dots \\
&\frac{\max(D_1 + 1 \cap D_2 + 1|H_1)}{\max(D_1 + 1 \cap D_2 + 1|H_1) + \min(D_1 \cap D_2|H_2)} \\
&= \frac{5}{5+5}, \dots, \frac{7}{7+2} \\
&\approx \{0.5, \dots, 0.777\}
\end{aligned} \tag{2.16}$$

$$\begin{aligned}
P(H_1|D_1 \cap D_2) &= \\
&\frac{\min(D_1 \cap D_2|H_1)}{\min(D_1 \cap D_2|H_1) + \max(D_1 + 1 \cap D_2 + 1|H_2)} \\
&\dots \\
&\frac{\max(D_1 \cap D_2|H_1)}{\max(D_1 \cap D_2|H_1) + \min(D_1 + 1 \cap D_2 + 1|H_2)} \\
&= \left\{ \frac{4}{4+6}, \dots, \frac{6}{6+3} \right\} \\
&\approx \{0.4, \dots, 0.666\}
\end{aligned} \tag{2.17}$$

This approach also allows for multiple simultaneous allocations with no need for iteration. So, for instance, to make two simultaneous decisions it is only necessary to calculate the probability ranges resulting from designating both allocations to H_1 (2.18), both to H_2 (2.19), and one to each hypothesis (2.20). In this case the de-

cision $P(H_1|D_1+1 \cap D_2+1)$ (2.20) falls entirely within the target range of 0.44–0.75 and is, therefore, the least divergent. The most divergent outcome is to make both allocations to H_2 (2.19).

$$\begin{aligned}
P(H_1|D_1+2 \cap D_2+2) &= \\
&\frac{\min(D_1+2 \cap D_2+2|H_1)}{\min(D_1+2 \cap D_2+2|H_1) + \max(D_1 \cap D_2|H_2)} \\
&\dots \\
&\frac{\max(D_1+2 \cap D_2+2|H_1)}{\max(D_1+2 \cap D_2+2|H_1) + \min(D_1 \cap D_2|H_2)} \\
&= \left\{ \frac{6}{5+6}, \dots, \frac{8}{8+2} \right\} \\
&\approx \{0.545, \dots, 0.8\}
\end{aligned} \tag{2.18}$$

$$\begin{aligned}
P(H_1|D_1 \cap D_2) &= \\
&\frac{\min(D_1 \cap D_2|H_1)}{\min(D_1 \cap D_2|H_1) + \max(D_1+2 \cap D_2+2|H_2)} \\
&\dots \\
&\frac{\max(D_1 \cap D_2|H_1)}{\max(D_1 \cap D_2|H_1) + \min(D_1+2 \cap D_2+2|H_2)} \\
&= \left\{ \frac{4}{4+7}, \dots, \frac{6}{6+4} \right\} \\
&\approx \{0.364, \dots, 0.6\}
\end{aligned} \tag{2.19}$$

$$\begin{aligned}
P(H_1|D_1+1 \cap D_2+1) &= \\
&\frac{\min(D_1+1 \cap D_2+1|H_1)}{\min(D_1+1 \cap D_2+1|H_1) + \max(D_1+1 \cap D_2+1|H_2)} \\
&\dots \\
&\frac{\max(D_1+1 \cap D_2+1|H_1)}{\max(D_1+1 \cap D_2+1|H_1) + \min(D_1+1 \cap D_2+1|H_2)} \\
&= \left\{ \frac{5}{5+6}, \dots, \frac{7}{7+3} \right\} \\
&\approx \{0.455, \dots, 0.7\}
\end{aligned} \tag{2.20}$$

2.6 Research questions

This empirical research investigates the issues raised above in a consistent manner, aiming to minimise the potential for confounding variables which might arise from the use of different experimental formats and questions. Each experiment draws from the same six questions presented in the same way with, as appropriate, either two or three decision choices, and either two or four pieces of diagnostic information. These questions may be summarised as:

1. Determining the make of a friend's car;
2. Deciding to which political group a Member of the European Parliament belongs;
3. Determining from which of two nearby islands an archaeological find is most likely to have originated (after Doherty et al.);
4. Deciding with which mobile phone operator to take out a contract;
5. Deciding where to go on holiday;
6. Determining which electricity supplier to recommend to readers of a magazine.

Presentational screenshots may be found in Appendix B.1.

For consistency, all the experiments took place online with no participant exclusions. Although there was a submission validation process, e.g., to automatically exclude multiple submissions from the same IP address to reduce the likelihood of any participant completing an experiment more than once, no participants were excluded as a result. The full validation and security protocol is given in Appendix C. There was no collection of information which could identify participants, with the final octets of all IP addresses being automatically anonymised after each experiment to ensure compliance with all relevant European Union data protection legislation.

For experiments 1, 3 and 4, in order for the participants to be presented with diagnostic information that covered the entire sample space, all the prior and posterior data were randomly generated. This ensured that no bias could be inadvertently introduced as a result of poor experimental construction. At no point were the researchers aware of, or able to influence, the information given to participants. The integrity of the process was guaranteed by obtaining the random number sequences through the API at www.random.org.

The statistical analysis for each experiment is intentionally simple, with the chi-squared test used for inter-experimental comparison. Given that it is impossible to manipulate participants' decision-making strategy as an independent variable with any surety, the only metric considered is whether the recorded behaviour exhibits randomness and, if not, whether the results match the data selection patterns predicted for any information search strategy. Thus, there are no preconceived, analytically biasing assumptions made about participant behaviour. Rather, the exhibiting of non-random behaviour is only taken to indicate that the participants have displayed a consistent approach within their decision-making processes.

2.6.1 RQ1: Does the structure of the pseudodiagnosticity test affect data selection?

While Feeney et al. have shown that data selection patterns are sensitive to the rarity of information, the structure of the pseudodiagnosticity test itself has gone unconsidered. Specifically, providing the anchor information in $P(D_1|H_1)$, as opposed to other locations, might be a confounding variable which influences observed selection patterns given that the contingency tables otherwise possess a visual symmetry. This is more than a technical nicety since any structural influence on data selection may generate either Type I or Type II errors during search pattern analysis, call into question the robustness of previous research findings, and directly affect forward experimental design.

2.6.2 RQ2: Do selection strategies show a preference for a particular datum within a chosen hypothesis?

The Crupi et al. epistemological strategy, as well as the Information Theoretic and the Relational Information Theoretic models of the pseudodiagnosticity paradigm, suggest that the choice of datum within a chosen hypothesis is irrelevant. From this, it follows that only a display of random intra-hypothesis selection would facilitate the positing of either of these models as completely explanatory.

2.6.3 RQ3: Do people evaluate contingency data in a consistent way?

This might be the most fundamental research questions since it is only evidence for the consistent assessment of contingency table data which can support an expectation of consistency in data search strategy. Without evidence for the consistent evaluation of the same data between people, the only conclusion that can be reasonably reached is that either data selection is essentially random, or that is guided by an individuals subjective preference for, or cognitive bias towards, a particular decision-making strategy. As such, a marked variation in data assessment would indicate that any analysis of gross selection patterns is flawed due to the potential influence of optimal data requirements for any specific analytical approach.

2.6.4 RQ4: Do people make multiple simultaneous allocations in a consistent manner?

A strict Bayesian protocol for the updating of contingency data demands the consecutive and iterative making of multiple decisions. This results from the need to update the posterior data following an allocation decision, due to a new piece of evidence, before subsequent evidence may be considered. However, any support for the idea that people are able to make multiple contemporaneous decisions, i.e., to project forward beyond $t = t + 1$, would suggest their use of an alternative non-iterative approach, such as the comparison of contingency table state as suggested

by the Relational Information Theory approach, since this would imply that any updating of the posterior data is not being made solely with reference to the Bayesian likelihood ratio.

2.6.5 RQ5: Does extending the pseudodiagnosticity test to a large contingency table format demonstrate clearer selection strategies?

It is only possible to test for the two distinct one degree of freedom selection strategies identified by Relational Information Theory by either allowing for more than one selection choice in the 2×2 contingency table, or by using a larger table. Since a 2×3 table with two degrees of selection freedom would allow for a strategy which just samples from each hypothesis, the number of differentiating characteristics must increase. For consistency in the decision-maker only knowing 50% of the data prior to making a decision, this means that the minimum size for a larger contingency table must be one with two hypotheses and four differentiating characteristics.

2.7 Experiment 1: Research questions 1 & 2

This experiment investigated the effect of “anchor information” position on data selection. Existing research has formalised the placement of this datum in $D_1|H_1$. Given the consequential lack of visual symmetry, this placement may inadvertently bias selection patterns. The pattern of intra-hypothesis selection is also considered.

2.7.1 Participants

The participants ($n = 150$) were recruited through University based social media networks, such as Facebook and LinkedIn groups. A number of Twitter mentions, primarily from IBM employees, also aided participant recruitment. The results comprise those of the first 150 participants who completed the experimental exercises. There were no exclusions and there was no inducement to participate.

2.7.2 Design, materials, and procedure

Using a publicly accessible online experimental format, participants were presented with two decision-making tasks constructed using two hypotheses with two diagnostic criteria. The questions asked were randomly selected from the available set of six questions, however no question could be asked of the same participant twice. In all cases the prior, “base-rate” information, as well as one piece of diagnostic information from the first diagnostic criteria, was provided. For the first question the “anchor” information was randomly allocated to either H_1 or H_2 , with the second question taking the alternative allocation. The participants were instructed to reveal one more datum before making a decision. All the prior and posterior information was randomly generated using the API at www.random.org. The questions presented to each participant, the initial contingency table for each of those questions, and the participants’ data selections may be found in Appendix D.1.

2.7.3 Results and discussion

Figure 2.8 gives the sensitivity of absolute cell selection patterns, as percentages, for “anchor information” placement in $D_1|H_1$ and $D_1|H_2$. When the anchor information was given $D_1|H_1$ a chi-squared test reveals a significantly non-random selection pattern, $\chi^2(2, N = 100) = 7.44$, $p = 0.024$. However, when the “anchor information” was given in $D_1|H_2$ selection choice becomes highly random $\chi^2(2, N = 100) = 1.34$, $p = 0.512$. This result suggests that the provision of the “anchor information” in $D_1|H_1$ within the standard pseudodiagnosticity paradigm is a structural element which has significant influence on cell selection. Noticeably, the change in selection rate was between $D_2|H_1$ and $D_2|H_2$, with selection of the paired cell to the “anchor information” being stable. For future experimental design, this result strongly suggests that the location of the “anchor information” should be counter-balanced between the available hypotheses to avoid potential Type-I and Type-II errors.

There was no significant difference in intra-hypothesis selection patterns between D_1 and D_2 for the alternate hypothesis.

Anchor $D_1 H_1$			Anchor $D_1 H_2$		
	H_1	H_2		H_1	H_2
D_1	-	35%	D_1	37%	-
D_2	21%	43%	D_2	35%	28%

Figure 2.8: Data selection patterns by “anchor information” placement.

2.8 Experiment 2: Research questions 3 & 4

The purpose of this experiment was to investigate whether there was consistency in the way that diagnostic data was interpreted, and if the inclusion of time as a variable lead to an iterative Bayesian series of allocations to the same hypothesis or a Relational Information Theoretic allocation to both hypotheses. If there was no consistency in the interpretation of data, then it would seem hard to posit that there should be a uniform approach to information search given that different analytic approaches may demand the selection of different data.

2.8.1 Participants

The participants ($n=50$) were psychology undergraduate students at the University of Surrey. The results comprise those of the first 50 participants who completed the experimental exercises. There were no exclusions. The award of a partial course credit acted as an inducement to some students to take part.

2.8.2 Design, materials, and procedure

Using a publicly accessible online experimental format, an alternating division of participants created two participant groups. Following Doherty et al., both groups had to identify from which of two islands archaeological finds originated. However, while the instructions for the first group asked for a decision regarding only one find, the second group had to make simultaneous decisions about two identical finds. The contingency tables followed the standard Doherty et al. pseudodiagnosticity format of two hypotheses and two diagnostic criteria, with the participants being given the

prior, “base-rate” information for each hypothesis along with one diagnostic, “anchor” datum. The participants revealed one more datum before reaching a decision.

The two hypotheses took randomly allocated, mutually exclusive prior values of either “9” or “10”. All the posterior diagnostic data equalled 50%. Consequently, the only useful diagnostic information available to the participants was the prior data.

For group 1, encoding of the participant decisions took either “1” when consistent with the larger prior hypothesis, or “0” when consistent with the smaller prior hypothesis. For group 2, the encoding was either “0” if both allocations favoured the smaller prior hypothesis, “1” if they both favoured the larger prior hypothesis, or “2” if divided between the hypotheses.

2.8.3 Results and discussion

For group one, 18 of the 25 participants allocated the find to the larger prior hypothesis. When compared to a random distribution this gives $\chi^2(1, N = 25) = 4$, $p = 0.0455$ (Yates’ p-value, corrected for continuity).

For group two, 23 of the 25 participants allocated one find to each hypothesis. When compared to a random decision selection this gives $\chi^2(2, N = 25) = 38.963$, $p < 0.0001$.

The results for group one suggest that there was a significantly consistent interpretation of contingency data. Perhaps surprisingly, the allocation of the archaeological find to the larger prior hypothesis is consistent with both the Bayesian and Relational Information Theoretic strategies rather than the “gambler’s fallacy” belief that the occurrence of events must even out. However, the highly significant result for group two, which required the allocation of archaeological finds to $t = t + 2$, is only consistent with Relational Information Theory. This result suggests that the participants were aware of the overall structure of the contingency table and the

need to maintain the statistical relationships within it in any forward projection.

2.9 Experiment 3: Research question 5

This experiment considered selection patterns within a larger, 2×4 , contingency table. Both the epistemological approach of Crupi et al., as well as standard Information Theory, would suggest that data selection strategy should remain entirely consistent over all degrees of freedom. However, the Relational Information Theory interpretation predicts that the final selection should demonstrate a strategy inversion that helps constrain the estimated probability range.

2.9.1 Participants

The participants ($n = 150$) were recruited through University based social media networks, such as Facebook and LinkedIn groups. A number of Twitter mentions, primarily from IBM employees, also aided participant recruitment. The results comprise those of the first 150 participants who completed the experimental exercises. There were no exclusions and there was no inducement to participate.

2.9.2 Design, materials, and procedure

Using a publicly accessible online experimental format, participants were presented with two decision-making tasks constructed using three hypotheses with four diagnostic criteria. The questions asked were randomly selected from the available set of six questions, however no question could be asked of the same participant twice. In all cases the prior, “base-rate” information, as well as one piece of diagnostic information from the first diagnostic criteria, was provided. Following the findings of Experiment 1, for the first question the “anchor” information was randomly allocated to either H_1 or H_2 with the second question taking the alternate allocation. All the prior and posterior data was randomly generated using the API at www.random.org. The participants were instructed to reveal three more data points before making a decision. The questions presented to each participant, the initial contingency table for each of those questions, and the participants’ data selections may be found in Appendix D.2.

2.9.3 Results and discussion

Table 2.4 gives the total recorded and expected choices for each of the three selections made by each participant in their two tasks. The “consistent” and “inconsistent” predictions reflect the hypothesis selection expected by Information Theory, with the chances of that selection being correct calculated as being the number of unknown data within the expected hypothesis against the total number of unknown data within the entire contingency table. This probability was calculated for each participant and reflects the choices they made at each stage. The expected figures are the number of selections that would have been made for each hypothesis if the choice was entirely random. Where the information theoretic value of two or more hypotheses was the same, with no prediction made as a consequence, that choice has been excluded from the results and has led to the total number of selections recorded being lower than 300.

The results show that for the first two selections the participants broadly followed an Information Theoretic strategy. While this strategy changed on the final, third selection there was no obvious preference for strong or weak information ($\chi^2(1, N=299)=0.31, p=0.5788$; Yates’ p-value, corrected for continuity).

<u>First selection</u>					<u>Second selection</u>				
Chances	Consistent	(Expected)	Inconsistent	(Expected)	Chances	Consistent	(Expected)	Inconsistent	(Expected)
3/7	31	(50.6)	87	(67.4)	2/6	14	(10.3)	17	(20.7)
4/7	139	(102.9)	41	(77.1)	3/6	134	(110.0)	86	(110.0)
					4/6	18	(28.7)	25	(14.3)
Total	170	(153.5)	128	(144.5)	Total	166	(149.0)	128	(145.0)
$\chi^2(1, N = 298) = 3.66, p = 0.0558^*$					$\chi^2(1, N = 294) = 3.93, p = 0.0474^*$				
<u>Third selection</u>									
Chances	Consistent	(Expected)	Inconsistent	(Expected)					
1/5	12	(3.0)	3	(12.0)					
2/5	36	(56.8)	106	(85.2)					
3/5	93	(70.8)	25	(47.2)					
4/5	4	(19.2)	20	(4.8)					
Total	145	(149.8)	154	(149.2)					
$\chi^2(1, N = 299) = 0.31, p = 0.5788^*$									

Table 2.4: Predicted Information Theory selections vs. actual selections for the 3 consecutive choices made in a 2×4 contingency table.

Note: *The calculated value of χ^2 has been corrected for continuity.

2.10 Experiment 4: Research question 5

Following the findings of Experiment 3, this experiment considered selection patterns within a large, 3×4 , contingency table where the increased number of hypotheses aimed to reduce the occurrence of pattern based selection strategies. Once again, both the epistemological approach of Crupi et al., as well as standard Information Theory, would suggest that data selection strategy should remain entirely consistent over all degrees of freedom. However, the Relational Information Theory interpretation predicts that the final selection should demonstrate a strategy inversion that helps constrain the estimated probability range.

2.10.1 Participants

The participants ($n = 150$) were recruited through University based social media networks, such as Facebook and LinkedIn groups. A number of Twitter mentions, primarily from IBM employees, also aided participant recruitment. The results comprise those of the first 150 participants who completed the experimental exercises. There were no exclusions and there was no inducement to participate.

2.10.2 Design, materials, and procedure

Using a publicly accessible online experimental format, participants were presented with two decision-making tasks constructed using three hypotheses with four diagnostic criteria. The questions asked were randomly selected from the available set of six questions, however no question could be asked of the same participant twice. In all cases the prior, “base-rate” information, as well as one piece of diagnostic information from the first diagnostic criteria, was provided. Following the findings of Experiment 1, for the first question the “anchor” information was randomly allocated to either H_1 , H_2 , or H_3 with the second question randomly taking one of the alternate allocations. All the prior and posterior data was randomly generated using the API at www.random.org. The participants were instructed to reveal five more data points before making a decision. The questions presented to each participant, the initial contingency table for each of those questions, and the participants’ data selections may be found in Appendix D.3.

2.10.3 Results and discussion

Table 2.5 gives the total recorded and expected choices for each of the five selections made by each participant in their two tasks. The “consistent” and “inconsistent” predictions reflect the hypothesis selection expected by Information Theory, with the chances of that selection being correct calculated as being the number of unknown data within the expected hypothesis against the total number of unknown data within the entire contingency table. This probability was calculated for each participant and reflects the choices they made at each stage. The expected figures are the number of selections that would have been made for each hypothesis if the choice was entirely random. Where the information theoretic value of two or more hypotheses was the same, with no prediction made as a consequence, that choice has been excluded from the results and has led to the total number of selections recorded being lower than 300.

The results show that for the first four selections the participants followed an Information Theoretic strategy with a high degree of significance. This strategy changed on the final, fifth selection which showed a significant aversion to the weakest information ($\chi^2(1, N = 292) = 6.82, p = 0.009$; Yates’ p-value, corrected for continuity) and a significant preference for the second weakest hypothesis ($\chi^2(1, N = 246) = 4.665, p = 0.0308$; Yates’ p-value, corrected for continuity). This change in strategy for the final selection is consistent with Relation Information Theory. Indeed, Relational Information Theory is the only approach which predicts this change. The final selection preference for the stronger of the two weak hypotheses may be due to the dismissal of the weakest hypothesis as a likely outcome, the concatenation of the weak hypotheses into one opposing hypothesis, or simply that this choice provides richer knowledge of the “middle” likelihood hypothesis from which inferences may be drawn about the weakest hypothesis. Given the strength of these findings it is difficult to conceive of alternative explanations for the selection strategy reversal. While the participants may have arbitrarily assigned $p_x = 0.5$, MaxEnt distributions to unknown data, and randomised their final datum selection

due to, for instance, experimental fatigue, the significant bias towards selecting the “middle” likelihood hypothesis would suggest that this preference reversal is a genuine phenomenon.

The findings of Experiments 3 and 4 suggest that the minimum sized contingency table required to analyse data selection patterns is one consisting of three hypotheses and four diagnostic data.

First selection				Second selection					
Chances	Consistent	(Expected)	Inconsistent	(Expected)	Chances	Consistent	(Expected)	Inconsistent	(Expected)
3/11	24	(24.0)	64	(64.0)	2/10	9	(4.0)	11	(16.0)
4/11	112	(72.7)	88	(127.3)	3/10	51	(51.9)	122	(121.1)
					4/10	67	(38.4)	29	(57.6)
Total	136	(96.7)	152	(191.3)	Total	127	(94.3)	162	(194.7)
	$\chi^2(1, N = 288) = 23.44, p < 0.0001^*$				$\chi^2(1, N = 289) = 16.33, p < 0.0001^*$				
Third selection				Fourth selection					
Chances	Consistent	(Expected)	Inconsistent	(Expected)	Chances	Consistent	(Expected)	Inconsistent	(Expected)
1/9	9	(0.9)	0	(8.1)	1/8	9	(2.1)	8	(14.9)
2/9	23	(12.8)	35	(45.2)	2/8	34	(26.8)	73	(80.2)
3/9	83	(62.4)	104	(124.6)	3/8	67	(50.2)	67	(73.8)
4/9	12	(16.0)	24	(20.0)	4/8	18	(16.5)	15	(16.5)
Total	127	(92.1)	163	(197.9)	Total	128	(95.6)	163	(195.4)
	$\chi^2(1, N = 290) = 18.83, p < 0.0001^*$				$\chi^2(1, N = 291) = 15.85, p < 0.0001^*$				
Fifth selection (a)				Fifth selection (b)					
(Prediction for strongest information theoretic data)				(Prediction for weakest information theoretic data)					
Chances	Consistent	(Expected)	Inconsistent	(Expected)	Chances	Consistent	(Expected)	Inconsistent	(Expected)
1/7	11	(4.5)	21	(27.5)	1/7	3	(2.9)	17	(17.1)
2/7	31	(37.7)	101	(94.3)	2/7	8	(31.4)	102	(78.6)
3/7	52	(43.3)	49	(57.7)	3/7	62	(59.6)	77	(79.4)
4/7	11	(14.9)	15	(11.1)	4/7	12	(13.1)	11	(9.9)
Total	105	(100.2)	186	(190.8)	Total	85	(107)	207	(185)
	$\chi^2(1, N = 291) = 0.28, p = 0.5967^*$				$\chi^2(1, N = 292) = 6.82, p = 0.009^*$				
Fifth selection (c)									
(Prediction for middle strength information theoretic data)									
Chances	Consistent	(Expected)	Inconsistent	(Expected)					
1/7	14	(4.1)	15	(24.9)					
2/7	29	(34.3)	91	(85.7)					
3/7	51	(39.9)	42	(53.1)					
4/7	3	(2.3)	1	(1.7)					
Total	97	(80.6)	149	(165.4)					
	$\chi^2(1, N = 246) = 4.665, p = 0.0308^*$								

Table 2.5: Predicted Information Theory selections vs. actual selections for the 5 consecutive choices made in a 3×4 contingency table.

Note: *The calculated value of χ^2 has been corrected for continuity.

2.11 General discussion

Relational Information Theory stresses the value of the relationships between ordinal data and argues that they have a numerical value within the decision-making process. Modelling shows that data selection following a simple “pick the biggest unknown” heuristic, derived from standard information theoretic entropy calculations, provides a probability range which may be constrained through a final selection of an informationally weaker datum. This is a natural consequence of set theory. Further, for decisions which require the updating of contingency data once the decision has been made, Relational Information Theory shows how it is an understanding of the probabilistic data as a complete and integrated statistical system which allows for the forward projection of the system state to a future point. In the absence of knowledge about how the system develops, this projection derives from the least statistically disruptive set of decisions. Thus, the purpose of data selection is to create a mental representation of the decision-making task as close to the unknown original as possible. This contrasts with the standard Bayesian approach which, without decision verification, may lead to the same decisions being made repeatedly with an ever increasing degree of certainty.

The empirical results suggest that Relational Information Theory is also descriptive of human diagnostic decision-making. Experiment 2 demonstrates that when asked to make multiple simultaneous allocations there was an overwhelming participant decision preference consistent with the principle of forward state projection. Equally, Experiment 4 shows then when given an appropriate number of degrees of freedom for their data search strategy, participant selections were consistent with the predictions made by Relational Information Theory to a highly significant degree. This significance extended to the predicted change of strategy for the final datum selection.

The central premise of the pseudodiagnosticity paradigm is that the selection of non-paired information demonstrates illogicality. While the previously discussed computational model has shown that an information search strategy based solely on the selection of data pairs is not normative when making categorical decisions,

the empirical results of the research questions also suggest that there are structural problems with two hypotheses and two diagnostic criteria matrices normally used in pseudodiagnosticity research. Indeed, not only are cell selection patterns within a two hypothesis, two diagnostic criteria contingency table influenced by presentation, but this format also creates a conflict between gaining knowledge by selecting a datum on information theoretic grounds and seeking to constrain the potential probability range. This would suggest that findings based upon this format are either dependent upon, or are the result of, a biased experimental structure. As a consequence, any assertions regarding illogical cognitive processes which arise from research based on this structure must be viewed with a certain degree of circumspection.

There is an important implication which arises from the apparent change in strategy for the final data selection. If this change in strategy had arisen at the point that a decision was made, with the participant no longer needing to gain further knowledge by following a purely epistemological or entropy driven search strategy, then it would be strongly indicative of hypothesis testing. However, since there is a clear preference for informationally weak data in the final selection, which is consistent with the idea of constraining probability ranges, this research supports the conclusions elsewhere that hypothesis testing does not happen. But, unlike other research, the Relational Information Theory approach demonstrates that the failure to test hypotheses is not a symptom of cognitive dysfunction but, rather, that it shows the construction of a mental representation of the problem. In this there can be no conclusion of confirmation bias within the decision-making process, only that instead of decisions being a continual, on-going process they are, instead, events which only occur once contingency data and the relationships between them have been understood, as far as is possible, by the decision-maker. Relational Information Theory may, therefore, be seen to be a formalized version of the test strategy of Klayman and Ha (1987), and helps link the “information gain” perspective of Oaksford and Chater (1994, 1995) with the mental models approach of Johnson-Laird (1983) by creating a unified framework that includes statistical, semantic, and structural information.

2.12 Conclusion

By rejecting the notion of information systems as being a series of independent “facts”, this chapter proposes a different normative and descriptive account of diagnostic decision-making which is supported by both theoretical and empirical work. In this, the emphasis is placed on the knowledge derived from the relationships between ordinal data. However, this approach is not epistemological. These relationships are shown to have significant numerical worth, and it is their discovery which drives information search.

The central assertions of the pseudodiagnosticity paradigm that only paired data have diagnostic worth, that the selection of data pairs is normatively correct, and that the tendency to select non-paired data may only be explained as a failure of logic have been challenged not only through computational modeling but, also, through the development of the Relational Information Theory model. Thus, it has been clearly demonstrated that there exists an alternative strategy that is not only more effective than the selection of paired data but is also normatively correct. That there is also evidence to support the idea that people actively follow this strategy in information search strongly suggests that data selection is neither illogical nor the result of confirmation bias.

The structural problems with the standard two hypotheses and two diagnostic criteria pseudodiagnosticity exercises have been highlighted, with the presence of anchor information in $D_1|H_1$ being shown to strongly influence cell selection patterns. It is only by extending the exercises to include at least three hypotheses that these influences appear to be largely negated, with clear selection patterns and strategies starting to emerge.

Chapter 3

A conjecture for the quantum calculation of likelihood ratios

3.1 Introduction

One problem with the pseudodiagnosticity paradigm, discussed in Chapter 2, is its reliance upon categorical answers to questions framed as Bayesian problems. While this experimental structure affords the decision-maker an opportunity to use non-Bayesian techniques to provide reasonable answers to questions, the axiomatic difficulties associated with the naïve Bayes' classifier raise questions about how estimations of probability should be calculated if required. In particular, the reliance of Bayes' theorem upon the multiplication of marginal probabilities, in the absence of statistical information such as estimates of covariate overlap, is problematic if the conditional independence of the posterior data is not guaranteed.

Such issues have led some researchers to attempt to reconceptualise psychology and decision-making theory using quantum mechanics - an approach with intuitive merit given that both disciplines apply statistical axioms to analyse and interpret probabilistic systems. For instance, Busemeyer and Bruza (2012) have considered the effects of state transitions within a quantum, Hilbert space to describe how the order in which relevant information is considered may affect product choice. Equally, Khrennikov (2009) has used a quantum mechanical approach to explain psychological phenomena such as the violation of the law of total probability. How-

ever, within psychological theory there has been no attempt to consider the topic of Bayesian rationality within a quantum framework.

A promising starting point for the application of quantum mechanics to Bayesian rationality is the Lüders (1951) postulate, which allows for the estimation of particle correlations through state projection. However, the Lüders’ postulate fails under nonlocal conditions, such as the Einstein, Podolsky, and Rosen paradox (Graft, 2017). Thus, at best, the Lüders’ postulate is a special case expression designed solely for use with sub-atomic particle ensembles (Graft, 2017), rather than the more common individual measurements associated with decision-making theory.

An alternative theoretical approach is that of Caves et al. (2002a) who have taken a radically subjectivist view of Bayes’ theorem by applying de Finetti’s epistemologically driven view of statistics (see de Finetti, 1974). In doing so, Caves et al. have argued that their “quantum Bayesian” statistical systems are best interpreted by methods in which the Bayesian likelihood ratio is seen to be both external to the system and subjectively imposed on it by the observer (Timpson, 2008). However, from a decision-making perspective, the Caves et al. approach is problematic. Bayes’ theorem and, in particular, the naïve Bayes’ classifier have been used extensively to interpret information systems and develop normative decision-making models (Oaksford and Chater, 2007). While subjectivity may play a role in a descriptive model of human decision-making, its use in normative analysis could suggest the presence of a cognitive “homunculus” with the power to influence decision outcomes. Yet at a human scale, for instance, an observer’s belief as to the chances of a fair coin landing either “heads” or “tails” has no known effect. Rather, within normative decision-making theory, the “heads:tails” likelihood ratio of 0.5:0.5 is only meaningful when considered as a property of the coin’s own internal statistical system rather than as some ephemeral and arbitrary qualia.

Despite the evident progress made in the application of quantum mechanics to decision-making theory, the lack of an orthodox Copenhagen-based theoretical counterpoint to Caves et al. has impeded the development of new, non-subjective, and

normative decision-making models in psychology. It is this knowledge gap which this chapter aims to fill.

3.2 The limits of Bayes' theorem

Returning to the example contingency table presented in Figure 2.1, the simplest approach to calculating a likelihood ratio is to naïvely ignore any intersection, or co-dependence, of the data and directly multiply the marginal probabilities (see, e.g., Doherty et al., 1979; Feeney et al., 2008; D'addario and Macchi, 2012). Hence, given Figure 2.1, the likelihood of Street A having the greatest number of houses with both a blue front door and a garage would be calculated as

$$\begin{aligned} P(H_1|D_1 \cap D_2) &= \frac{0.5 \times 0.8 \times 0.6}{(0.5 \times 0.8 \times 0.6) + (0.5 \times 0.7 \times 0.5)} \\ &\approx 0.578 . \end{aligned} \tag{3.1}$$

Yet, because the data intersect, this probability value is only one of a number which may be reasonably calculated. Alternatives include calculating a likelihood ratio using the mean value μ of the frequency ranges for each hypothesis given in (2.13), calculated using (2.12),

$$\begin{aligned} P(\mu[n(D_1 \cap D_2|H_1)]) &= \frac{1}{10} \times \frac{1}{3}(4 + 5 + 6) = 0.5 , \\ P(\mu[n(D_1 \cap D_2|H_2)]) &= \frac{1}{10} \times \frac{1}{4}(2 + 3 + 4 + 5) = 0.35 \\ \Rightarrow P(H_1|\mu D_1 \cap D_2) &\approx 0.588 ; \end{aligned} \tag{3.2}$$

and taking the mean values of the same probability ranges,

$$\begin{aligned} \min P(H_1|D_1 \cap D_2) &= \frac{4}{4 + 5} , \\ \max P(H_1|D_1 \cap D_2) &= \frac{6}{6 + 2} \\ \Rightarrow \mu[P(H_1|D_1 \cap D_2)] &\approx 0.597 . \end{aligned} \tag{3.3}$$

Given this multiplicity of probability values, it would seem that none of these

methods may lay claim to normativity if the conditional independence of contingency data cannot be guaranteed. This problem of covariate overlap has, of course, been previously addressed within statistical literature. For instance, the “maximum likelihood” approach of Dempster et al. (1977) has demonstrated how an “expectation-maximization” algorithm may be used to derive appropriate covariate overlap measures. Indeed, the mathematical efficacy of this technique has been confirmed by Wu (1983). However, given both the computational complexity and iterative nature of this solution, where each iteration requires sequential expectation and maximisation stages (see Ramachandran and Tsokos, 2009), its psychological plausibility as being descriptive of human decision-making is open to question. This is especially true given people’s reliance on heuristics rather than cognitively expensive exactitudes (Kahneman, 2011). Since there is also little evidence that the naïve Bayes’ classifier forms any part of the human decision-making process (Doherty et al., 1979), the theoretical advancement of the psychology of decision-making demands a mathematical approach in which covariate overlaps can be automatically, and directly, calculated from contingency data using a methodology that is as assumption-free as possible. Such non-subjective measures of covariate overlaps would find immediate application not just in the calculation of Bayes’ likelihood ratios, but also in general Bayesian methodology where, for instance, they could represent the “edge” conditional relationships between nodes in Bayesian networks when the precise nature of inter-nodal conditionality is unknown (see, e.g., Darwiche, 2009).

3.3 A quantum mechanical proof of Bayes’ theorem for conditionally independent data

While classical probability theory depends upon the Kolmogorov statistical axioms and their use of joint probability spaces, the quantum mechanical von Neumann axioms offer an alternative mathematical approach based on vector spaces, such as the Hilbert space or Bloch sphere (see, e.g., Griffiths and Harris, 1995). Here, the von Neumann axioms reject the idea of events having discrete probabilities in favour of their representation as vectors with direction rather than fixed values.

These vectors are usually expressed using the Dirac “bra-ket” notation (see Dirac, 1939), and interpreted using matrix mathematics. In this, the vertical matrix “kets”, written as “ $|\rangle$ ”, form part of a vector space with their equivalent transpositions into horizontal matrices, known as “bras”, being written as “ $\langle|$ ”. Such a transposition is known as the “Hermitian conjugate” and is denoted hereafter with an asterisk, so that if

$$\langle\alpha|\beta\rangle = \phi, \text{ then } \langle\beta|\alpha\rangle = \phi^* . \quad (3.4)$$

From matrix mathematics, it follows that the product of any ket multiplied by its own bra is 1. This is normally interpreted to mean that the ket and bra are “orthonormal”, i.e., that their product is 1, and that they are orthogonal, or perpendicular, to each other thereby forming a right angle. The sum of all the kets within a vector space gives the system state, or system wave function, and is orthonormalised using $\frac{1}{\sqrt{N}}$ so that the value of the system, often denoted as $|\Psi\rangle$, is 1.

However, there are many conceptual difficulties that can arise in the implementation of the von Neumann axioms. For instance, a Dirac representation of Figure 2.1 as a standard quantum superposition, i.e., as the logical addition of H_1 and H_2 , is

$$\begin{aligned} |\Psi\rangle = \frac{1}{\sqrt{N}} \Big[& \alpha \left(\sqrt{\frac{1}{3}} |4\rangle_{H1} + \sqrt{\frac{1}{3}} |5\rangle_{H1} + \sqrt{\frac{1}{3}} |6\rangle_{H1} \right) \\ & + \beta \left(\sqrt{\frac{1}{4}} |2\rangle_{H2} + \sqrt{\frac{1}{4}} |3\rangle_{H2} + \sqrt{\frac{1}{4}} |4\rangle_{H2} + \sqrt{\frac{1}{4}} |5\rangle_{H2} \right) \Big] . \end{aligned} \quad (3.5)$$

In this instance, (3.5) cannot be solved since the possible values for each hypothesis (see 2.12) have been described as equal chance outcomes within the superposition, with the unknown, and non-derivable, coefficients α and β assuming the role of the classical Bayesian likelihood ratio.

Instead, progress may be made by rewriting Bayes’ theorem itself as a quantum mechanical expression. If the contingency table is re-expressed in such a way as to include the covariate intersections, but without changing its internal statistical structure, then such a rewriting might allow for statistical analysis with few, non-arbitrary assumptions. For instance, the re-conceptualisation of covariate data as a

quantum entangled system could replicate the underlying assumption of Bayes' theorem that a non-trivial dependency exists between data and their allotted hypothesis (see, e.g., Ramachandran and Tsokos, 2009) by creating kets from the entanglement of the hypotheses with their contingent data. Here, "entanglement" takes a standard definition to refer two wave functions, i.e., kets, being correlated in such a way that it is impossible to describe one independently of the other (see, e.g., Griffiths and Harris, 1995). Conceptually, this means that although the two elements of the entanglement can exist independently of each other, their descriptions rely upon each other. Thus, where "a street" and "houses" are distinct logical constructs, "a street with houses" and "houses on a street" can only be defined through their mutually dependent relationship. This use of entanglement directly duplicates the assumption of Bayes' theorem that there is a non-trivial dependency between a datum and its associated hypothesis. The usual notation for an entangled system is the Kronecker product, written as " \otimes ".

To demonstrate the efficacy of this approach, and aid the development of a full quantum mechanical expression, it is first necessary to consider the simplest form of Bayes' theorem for the case of exclusive populations H_i and data sets D, \bar{D} , with even priors, such as given in Figure 3.1.

	Street A (H_1)	Street B (H_2)
Number of houses (n)	10 ($X1$)	10 ($X2$)
% blue front door (D)	0.8 ($x1$)	0.7 ($x2$)
% not blue front door (\bar{D})	0.2 ($y1$)	0.3 ($y2$)

Figure 3.1: Example contingency table for the case of exclusive data sets.

Here, the overall probability of H_1 , given that a house has a blue front door, may be easily calculated as

$$P(H_1|D) = \frac{n(D|H_1)}{n(D|H_1) + n(D|H_2)} . \quad (3.6)$$

The a priori uncertainty in Figure 3.1 may be expressed by constructing a wave

function in which the four data points are encoded as a linear superposition,

$$\begin{aligned} |\Psi\rangle = & \alpha_{1,1} |H_1 \otimes D\rangle + \alpha_{1,2} |H_1 \otimes \bar{D}\rangle \\ & + \alpha_{2,1} |H_2 \otimes D\rangle + \alpha_{2,2} |H_2 \otimes \bar{D}\rangle . \end{aligned} \quad (3.7)$$

Since there is no overlap between either D and \bar{D} or the populations H_1 and H_2 , each datum automatically forms an eigenstate basis with the orthonormal conditions

$$\begin{aligned} \langle H_1 \otimes D | H_1 \otimes D \rangle &= \langle H_1 \otimes \bar{D} | H_1 \otimes \bar{D} \rangle = 1 \\ \langle H_2 \otimes D | H_2 \otimes D \rangle &= \langle H_2 \otimes \bar{D} | H_2 \otimes \bar{D} \rangle = 1 \\ \text{all other bra-kets} &= 0 , \end{aligned} \quad (3.8)$$

where the normalization of the wave function demands that

$$\langle \Psi | \Psi \rangle = 1 , \quad (3.9)$$

so that the sum of the modulus squares of the coefficients $\alpha_{i,j}$ gives a total probability of 1

$$|\alpha_{1,1}|^2 + |\alpha_{1,2}|^2 + |\alpha_{2,1}|^2 + |\alpha_{2,2}|^2 = 1 . \quad (3.10)$$

(3.10) follows from Born's rule (Born, 1954) which takes the probability of a wave function as being the square of its amplitude.

Let

$$\begin{aligned} x_1 &= P(D|H_1), \quad y_1 = P(\bar{D}|H_1) , \\ x_2 &= P(D|H_2), \quad y_2 = P(\bar{D}|H_2) , \\ X_1 &= P(H_1), \quad X_2 = P(H_2) . \end{aligned} \quad (3.11)$$

If the coefficients $\alpha_{i,j}$ from (3.7) are set as required by Figure 3.1, it follows that

$$|\alpha_{1,1}|^2 = x_1, \quad |\alpha_{1,2}|^2 = y_1, \quad |\alpha_{2,1}|^2 = x_2, \quad |\alpha_{2,2}|^2 = y_2 , \quad (3.12)$$

so that the normalised wave function $|\Psi\rangle = 1$ and is described by

$$|\Psi\rangle = \frac{1}{\sqrt{N}}(\sqrt{x_1}|H_1 \otimes D\rangle + \sqrt{y_1}|H_1 \otimes \bar{D}\rangle + \sqrt{x_2}|H_2 \otimes D\rangle + \sqrt{y_2}|H_2 \otimes \bar{D}\rangle) \quad (3.13)$$

for some normalization constant N .

The orthonormality condition (3.9) implies that

$$N = x_1 + y_1 + x_2 + y_2 = X_1 + X_2, \quad (3.14)$$

thereby giving the full wave function description

$$|\Psi\rangle = \frac{\sqrt{x_1}|H_1 \otimes D\rangle + \sqrt{y_1}|H_1 \otimes \bar{D}\rangle + \sqrt{x_2}|H_2 \otimes D\rangle + \sqrt{y_2}|H_2 \otimes \bar{D}\rangle}{\sqrt{X_1 + X_2}}. \quad (3.15)$$

If the value of $P(H_1|D)$ is to be calculated, i.e., the property D is observed, then the normalized wave function (3.7) collapses, i.e., reduces, to

$$|\Psi'\rangle = \alpha_1 |H_1 \otimes D_1\rangle + \alpha_2 |H_2 \otimes D_1\rangle, \quad (3.16)$$

where the coefficients $\alpha_{1,2}$ may be determined by projecting $|\Psi\rangle$ on to the two terms in $|\Psi'\rangle$ using (3.8), giving

$$\begin{aligned} \alpha_1 &= \langle\Psi'|H_1 \otimes D\rangle = \sqrt{\frac{x_1}{X_1 + X_2}}, \\ \alpha_2 &= \langle\Psi'|H_2 \otimes D\rangle = \sqrt{\frac{x_2}{X_1 + X_2}}. \end{aligned} \quad (3.17)$$

Normalizing (3.16) with the coefficient N'

$$|\Psi'\rangle = \frac{1}{\sqrt{N'}}\left(\sqrt{\frac{x_1}{X_1 + X_2}}|H_1 \otimes D\rangle + \sqrt{\frac{x_2}{X_1 + X_2}}|H_2 \otimes D\rangle\right), \quad (3.18)$$

and using the normalization condition (3.9), implies that

$$1 = \langle \Psi' | \Psi' \rangle = \frac{1}{N'} \left(\frac{x_1}{X_1 + X_2} + \frac{x_2}{X_1 + X_2} \right)$$

$$\rightarrow N' = \frac{x_1 + x_2}{X_1 + X_2} . \quad (3.19)$$

Thus, after collapse, the normalized wave function (3.18) becomes

$$|\Psi'\rangle = \sqrt{\frac{x_1}{x_1 + x_2}} |H_1 \otimes D\rangle + \sqrt{\frac{x_2}{x_1 + x_2}} |H_2 \otimes D\rangle , \quad (3.20)$$

which means that the probability of observing $|H_1 \otimes D\rangle$ is

$$P(|H_1 \otimes D\rangle) = \left(\sqrt{\frac{x_1}{x_1 + x_2}} \right)^2 = \frac{\alpha_1^2}{\alpha_1^2 + \alpha_2^2} = \frac{x_1}{x_1 + x_2} . \quad (3.21)$$

This is entirely consistent with Bayes' theorem and demonstrates its derivation using quantum mechanical axioms.

3.4 A quantum mechanical expression to calculate likelihood ratios, with conditionally dependent data, for a 2×2 contingency table

Having established the principle of using a quantum mechanical approach for the calculation of simple likelihood ratios with mutually exclusive data as presented in Figure 3.1, it becomes possible to consider the general case of 2 hypotheses and 2 data (3.22), where the data are conditionally dependent, or intersect.

	H_1	H_2
D_1	$x_{1,1}$	$x_{1,2}$
D_2	$x_{2,1}$	$x_{2,2}$

(3.22)

Here the contingency table in (3.22) is indexed using

$$x_{i,\alpha} , \quad \alpha = 1, 2; \quad i = 1, 2 , \quad (3.23)$$

and taken to have a size of $n=2$ hypotheses and $m=2$ contingency data.

While the general wave function remains the same as before, the overlapping data, $D_1|H_x \cap D_2|H_x$, create non-orthonormal inner products which can be naturally defined as

$$\langle H_\alpha \otimes D_i | H_\beta \otimes D_j \rangle = c_{ij}^\alpha \delta_{\alpha\beta} , \quad c_{ij}^\alpha = c_{ji}^\alpha \in \mathbb{R} , \quad c_{ii}^\alpha = 1 , \quad (3.24)$$

and which, as real numbers, exist in a Euclidean space \mathbb{R} , rather than the orthonormal Hilbert space defined by the eigenstate bases of the contingency table data. That these inner-products are real is emphasised by setting their Hermitian conjugates to take the same values since it is necessarily true that $D_1|H_x \cap D_2|H_x = D_2|H_x \cap D_1|H_x$.

These inner products, c_{ij}^α , are usually interpreted as giving the probability amplitude of a ket collapsing into its Hermitian conjugate bra (see Strang, 1980) where, following Born's rule (see Born, 1954), the amplitude is taken to be equivalent to the square root of the actual probability. Assuming that the overlaps c_{ij}^α are real, then it is only possible for such a collapse to occur if both the bra and ket are the same. As such, they must provide a measure of the conditional dependence between the contingency data. Given that the contingency data are real, then the assumption that c_{ij}^α must also be real is not unreasonable. In other words, there must be a symmetry where $c_{ij}^\alpha = c_{ji}^\alpha$ for each α , and that for each α and i the state is normalized, i.e., $c_{ii}^\alpha = 1$. The given independence of the hypotheses H_α also enforces the Kronecker delta function, $\delta_{\alpha\beta}$, which returns 1 if $\alpha = \beta$ and 0 otherwise. In this, the Kronecker delta function acts as a logic gate allowing inner products derived from bra-ket combinations within the same hypothesis to take a value, while nullifying all others. In other words, the Kronecker delta function prevents the creation of inner-products between data which belong to mutually exclusive, and competing, hypotheses.

The Hilbert vector space V , described by the kets $|H_\alpha \otimes D_i\rangle$, is mn -dimensional and, because of the independence of H_α , naturally decomposes into the direct sum (3.25) with respect to the inner product, thereby demonstrating that the non-orthonormal conditions are the direct sum of m vector spaces V^α :

$$V = \text{Span}(\{|H_\alpha \otimes D_i\rangle\}) = \bigoplus_{\alpha=1}^n V^\alpha, \quad \dim V^\alpha = m. \quad (3.25)$$

That is to say that the Hilbert space for the entire contingency table is simply a linear combination of the series of Hilbert sub-spaces that may be created from the data, and inner-products, of each hypothesis. This is only made possible by the given independence of the hypotheses.

A full wave function description of the entire contingency table can only be created if, for each hypothesis, the sub-Hilbert space V^α and its associated inner-product Euclidean space \mathbb{R}^α are unified. This can be achieved using the Gram-Schmidt algorithm which orthonormalises any Hilbert space with respect to its inner-products (see Strang, 1980). In this way, a new, unified, and isomorphic representation of both the original Hilbert sub-space and its associated Euclidean sub-space may be returned. This new, orthonormal Hilbert sub-space is defined by the same number of base vectors as the original sub-space, and may be presented as

$$|K_i^\alpha\rangle = \sum_{k=1}^n A_{i,k}^\alpha |H_\alpha \otimes D_k\rangle, \quad \langle K_i^\alpha | K_j^\alpha \rangle = \delta_{ij}, \quad (3.26)$$

for each $\alpha = 1, 2, \dots, n$ with $m \times m$ matrices $A_{i,k}^\alpha$, for each α .

Substituting the inner products (3.24) gives

$$\sum_{k,k'=1}^m A_{ik}^\alpha A_{jk'}^\alpha c_{kk'}^\alpha = \delta_{ij} \quad \forall \alpha = 1, 2, \dots, n, \quad (3.27)$$

for all hypotheses. Thus, the wave-function may now be written as a linear combination of the orthonormalised kets $|K_i^\alpha\rangle$ with the coefficients b_i^α , and may be expanded

into the $|H_\alpha \otimes D_i\rangle$ basis using (3.26), i.e.,

$$|\Psi\rangle = \sum_{\alpha,i} b_i^\alpha |K_i^\alpha\rangle = \sum_{\alpha,i,k} b_i^\alpha A_{ik}^\alpha |H_\alpha \otimes D_k\rangle . \quad (3.28)$$

As with (3.12) from earlier, the coefficients in (3.28) should be set as required by the contingency table

$$\sum_i b_i^\alpha A_{i,k}^\alpha = \sqrt{x_{k\alpha}} , \quad (3.29)$$

where, to solve for the b -coefficients, (3.27) may be used to invert

$$\sum_{k,k'} \sum_i b_i^\alpha A_{ik}^\alpha A_{jk'}^\alpha c_{kk'}^\alpha = \sum_{k,k'} \sqrt{x_{k\alpha}} A_{jk'}^\alpha c_{kk'}^\alpha , \quad (3.30)$$

giving

$$b_j^\alpha = \sum_{k,k'} \sqrt{x_{k\alpha}} A_{jk'}^\alpha c_{kk'}^\alpha . \quad (3.31)$$

Having relabelled the indices as necessary, a back-substitution of (3.29) into the expansion (3.28) gives

$$|\Psi\rangle = \sum_{\alpha,i,k} b_i^\alpha A_{ik}^\alpha |H_\alpha \otimes D_k\rangle = \sum_{\alpha,k} \sqrt{x_{k\alpha}} |H_\alpha \otimes D_k\rangle , \quad (3.32)$$

which is equivalent to assigning each ket's coefficient to the square root of its associated entry in the contingency table.

The normalization factor for $|\Psi\rangle$ is $1/\sqrt{N}$, where N is the sum of the squares of the coefficients b of the orthonormalised bases $|K_i^\alpha\rangle$,

$$\begin{aligned} N &= \sum_{i,\alpha} (b_i^\alpha)^2 = \sum_{i,\alpha} b_i^\alpha \left(\sum_{k,k'} \sqrt{x_{k\alpha}} A_{ik}^\alpha c_{kk'}^\alpha \right) \\ &= \sum_{k,k',\alpha} \sqrt{x_{k\alpha} x_{k'\alpha}} c_{kk'}^\alpha . \end{aligned} \quad (3.33)$$

Thus, the final normalized wave function is

$$|\Psi\rangle = \frac{\sum_{\alpha,k} \sqrt{x_{k\alpha}} |H_\alpha \otimes D_k\rangle}{\sqrt{\sum_{i,j,\alpha} \sqrt{x_{i\alpha}x_{j\alpha}} c_{ij}^\alpha}}, \quad (3.34)$$

where α is summed from 1 to n , and i, j are summed from 1 to m . Note that, in the denominator, the diagonal term $\sqrt{x_{i\alpha}x_{j\alpha}} c_{ij}^\alpha$, which occurs whenever $i = j$, simplifies to $x_{i\alpha}$ since $c_{ii}^\alpha = 1$ for all α .

From (3.34) it follows that, exactly in parallel to the non-intersecting case, if all properties D_i are observed simultaneously, the probability of any hypothesis H_α , for a fixed α , is

$$P(H_\alpha | D_1 \cap D_2 \dots \cap D_m) = \frac{\sum_i (b_i^\alpha)^2}{\sum_{i,\beta} (b_i^\beta)^2} = \frac{\sum_{i,j} \sqrt{x_{i\alpha}x_{j\alpha}} c_{ij}^\alpha}{\sum_{i,j,\beta} \sqrt{x_{i\beta}x_{j\beta}} c_{ij}^\beta}. \quad (3.35)$$

In the case of non-even populations for each hypothesis (i.e., non-even priors), each element within (3.35) should be appropriately weighted.

3.5 Example solution for a 2×2 contingency table

Returning to the problem presented in the contingency table Figure 2.1, it is now possible to calculate the precise probability for a randomly selected house with the properties of “blue front door” and “garage” belonging to Street A (H_1). Unfortunately, plotting the contingency data from Figure 2.1, using (3.36), into c_1, c_2 space is unhelpful (see Figure 3.2). Thus, for the example 2×2 matrix, the general expression must be solved directly. Since $c_{ii}^\alpha = 1$ and $c_{ij}^\alpha = c_{ji}^\alpha$ (see 3.24), expression (3.35)

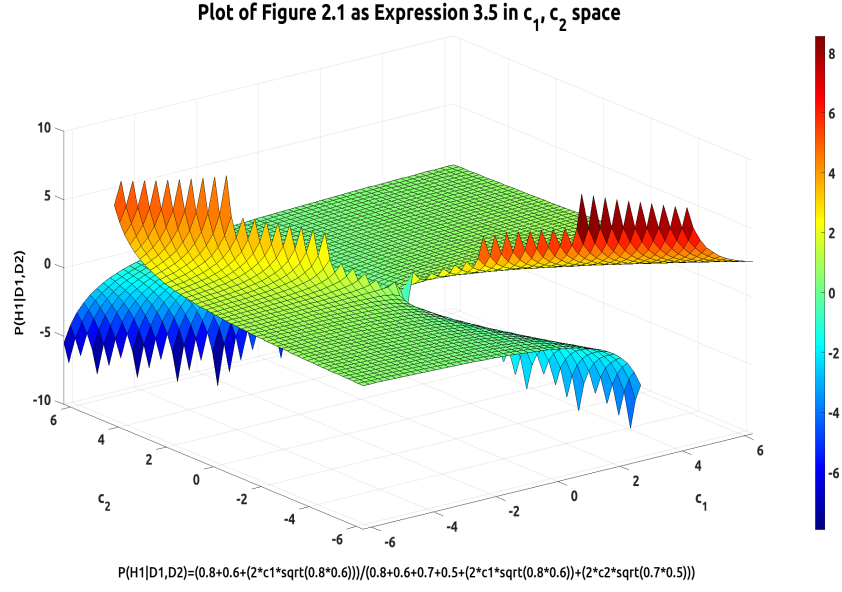


Figure 3.2: Plot of Figure 2.1 as Expression 3.36 in c_1, c_2 space.

may be written as

$$\begin{aligned}
 P(H_1|D_1 \cap D_2) &= \frac{\sum_{i,j=1}^2 \sqrt{x_{i,1} x_{j,1}} c_{ij}^1}{\sum_{i,j=1}^2 \sum_{\alpha=1}^2 \sqrt{x_{i\alpha} x_{j\alpha}} c_{ij}^\alpha} \\
 &= \frac{\sqrt{x_{1,1}^2} c_{1,1}^1 + \sqrt{x_{2,1}^2} c_{2,2}^1 + \sqrt{x_{1,1} x_{2,1}} c_{1,2}^1 + \sqrt{x_{2,1} x_{1,1}} c_{2,1}^1}{\sum_{\alpha=1}^2 \sqrt{x_{1,\alpha}^2} c_{1,1}^\alpha + \sqrt{x_{2,\alpha}^2} c_{2,2}^\alpha + \sqrt{x_{1,\alpha} x_{2,\alpha}} c_{1,2}^\alpha + \sqrt{x_{2,\alpha} x_{1,\alpha}} c_{2,1}^\alpha} \\
 &= \frac{x_1 + y_1 + 2c_1 \sqrt{x_1 y_1}}{x_1 + x_2 + y_1 + y_2 + 2c_1 \sqrt{x_1 y_1} + 2c_2 \sqrt{x_2 y_2}} , \tag{3.36}
 \end{aligned}$$

where, adhering to (3.11),

$$\begin{aligned}
 x_1 &= x_{1,1} = P(D_1|H_1), \quad y_1 = x_{2,1} = P(D_2|H_1) , \\
 x_2 &= x_{1,2} = P(D_1|H_2), \quad y_2 = x_{2,2} = P(D_2|H_2) , \\
 X_1 &= P(H_1), \quad X_2 = P(H_2) , \tag{3.37}
 \end{aligned}$$

and $c_1 := c_{1,2}^1$, $c_2 := c_{1,2}^2$. Implementing (3.36) is dependent upon deriving solutions for the yet unknown expressions c_i , $i = 1, 2$ which govern the extent of the intersection in (3.24). This can only be achieved by imposing reasonable constraints upon c_i which have been inferred from expected behaviour and known outcomes, i.e., through the use of boundary values and symmetries. Specifically, denoting $P(H_i|D_1 \cap D_2)$ as P_i , these constraints are:

Data dependence

The expressions c_i must, in some way, be dependent upon the data given in the contingency table, i.e.,

$$\begin{aligned} c_1 &= c_1(x_1, y_1, x_2, y_2; X_1, X_2) , \\ c_2 &= c_2(x_1, y_1, x_2, y_2; X_1, X_2) . \end{aligned} \quad (3.38)$$

Probability

The calculated values for P_i must fall between 0 and 1. Since x_i and y_i are positive, it suffices to take

$$-1 < c_i(x_1, y_1, x_2, y_2) < 1 . \quad (3.39)$$

Complementarity

The law of total probability dictates that

$$P_1 + P_2 = 1 , \quad (3.40)$$

which can be seen to hold.

Symmetry

The exchanging of rows within the contingency tables should not affect the calculation of P_i . In other words, for each $i = 1, 2$, P_i is invariant under $x_i \leftrightarrow y_i$. This constraint implies that

$$c_i(x_1, y_1, x_2, y_2) = c_i(y_1, x_1, y_2, x_2) . \quad (3.41)$$

Equally, if the columns are exchanged then P_i must map to each other, i.e., for each $i = 1, 2$ then $P_1 \leftrightarrow P_2$ under $x_1 \leftrightarrow x_2, y_1 \leftrightarrow y_2$ which gives the further constraint that

$$c_1(x_1, y_1, x_2, y_2) = c_2(x_2, y_2, x_1, y_1) . \quad (3.42)$$

Known values

There are a number of contingency table structures which give rise to a known probability, i.e.,

<table style="border-collapse: collapse;"> <tr><td style="border: none;"></td><td style="border: 1px solid black; padding: 2px 10px;">H_1</td><td style="border: 1px solid black; padding: 2px 10px;">H_2</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_1</td><td style="border: 1px solid black; padding: 2px 10px;">1</td><td style="border: 1px solid black; padding: 2px 10px;">1</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_2</td><td style="border: 1px solid black; padding: 2px 10px;">m</td><td style="border: 1px solid black; padding: 2px 10px;">n</td></tr> </table>		H_1	H_2	D_1	1	1	D_2	m	n	\rightarrow	$P_1 = \frac{m}{m+n}$	
	H_1	H_2										
D_1	1	1										
D_2	m	n										
<table style="border-collapse: collapse;"> <tr><td style="border: none;"></td><td style="border: 1px solid black; padding: 2px 10px;">H_1</td><td style="border: 1px solid black; padding: 2px 10px;">H_2</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_1</td><td style="border: 1px solid black; padding: 2px 10px;">m</td><td style="border: 1px solid black; padding: 2px 10px;">n</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_2</td><td style="border: 1px solid black; padding: 2px 10px;">1</td><td style="border: 1px solid black; padding: 2px 10px;">1</td></tr> </table>		H_1	H_2	D_1	m	n	D_2	1	1	\rightarrow	$P_1 = \frac{m}{m+n}$	
	H_1	H_2										
D_1	m	n										
D_2	1	1										
<table style="border-collapse: collapse;"> <tr><td style="border: none;"></td><td style="border: 1px solid black; padding: 2px 10px;">H_1</td><td style="border: 1px solid black; padding: 2px 10px;">H_2</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_1</td><td style="border: 1px solid black; padding: 2px 10px;">n</td><td style="border: 1px solid black; padding: 2px 10px;">m</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_2</td><td style="border: 1px solid black; padding: 2px 10px;">m</td><td style="border: 1px solid black; padding: 2px 10px;">n</td></tr> </table>		H_1	H_2	D_1	n	m	D_2	m	n	\rightarrow	$P_1 = \frac{1}{2}$	
	H_1	H_2										
D_1	n	m										
D_2	m	n										
<table style="border-collapse: collapse;"> <tr><td style="border: none;"></td><td style="border: 1px solid black; padding: 2px 10px;">H_1</td><td style="border: 1px solid black; padding: 2px 10px;">H_2</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_1</td><td style="border: 1px solid black; padding: 2px 10px;">n</td><td style="border: 1px solid black; padding: 2px 10px;">n</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_2</td><td style="border: 1px solid black; padding: 2px 10px;">m</td><td style="border: 1px solid black; padding: 2px 10px;">m</td></tr> </table>		H_1	H_2	D_1	n	n	D_2	m	m	\rightarrow	$P_1 = \frac{1}{2}$	
	H_1	H_2										
D_1	n	n										
D_2	m	m										
<table style="border-collapse: collapse;"> <tr><td style="border: none;"></td><td style="border: 1px solid black; padding: 2px 10px;">H_1</td><td style="border: 1px solid black; padding: 2px 10px;">H_2</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_1</td><td style="border: 1px solid black; padding: 2px 10px;">m</td><td style="border: 1px solid black; padding: 2px 10px;">m</td></tr> <tr><td style="border: 1px solid black; padding: 2px 10px;">D_2</td><td style="border: 1px solid black; padding: 2px 10px;">m</td><td style="border: 1px solid black; padding: 2px 10px;">m</td></tr> </table>		H_1	H_2	D_1	m	m	D_2	m	m	\rightarrow	$P_1 = \frac{1}{2} ,$	(3.43)
	H_1	H_2										
D_1	m	m										
D_2	m	m										

where m, n are positively valued probabilities. For such contingency tables the correct probabilities should always be returned by c_i . Applying this principle to

(3.36) gives the constraints

$$\frac{m}{m+n} = \frac{2c_1(m, 1, n, 1)\sqrt{m} + m + 1}{2c_1(m, 1, n, 1)\sqrt{m} + 2c_2(m, 1, n, 1)\sqrt{n} + m + n + 2} , \quad (3.44)$$

$$\frac{1}{2} = \frac{2c_1(n, m, m, n)\sqrt{m}\sqrt{n} + m + n}{2c_1(n, m, m, n)\sqrt{m}\sqrt{n} + 2c_2(n, m, m, n)\sqrt{m}\sqrt{n} + 2m + 2n} , \quad (3.45)$$

$$\frac{1}{2} = \frac{2c_1(n, m, n, m)\sqrt{m}\sqrt{n} + m + n}{2c_1(n, m, n, m)\sqrt{m}\sqrt{n} + 2c_2(n, m, n, m)\sqrt{m}\sqrt{n} + 2m + 2n} . \quad (3.46)$$

Non-homogeneity

Bayes' theorem returns the same probability for any linearly scaled contingency tables, e.g.,

$$x_1 \rightarrow 1.0, y_1 \rightarrow 1.0, x_2 \rightarrow 1.0, y_2 \rightarrow 0.50 \Rightarrow P_1 \approx 0.667 , \quad (3.47)$$

$$x_1 \rightarrow 0.5, y_1 \rightarrow 0.5, x_2 \rightarrow 0.5, y_2 \rightarrow 0.25 \Rightarrow P_1 \approx 0.667 . \quad (3.48)$$

While homogeneity may be justified for conditionally independent data, this is not the case for intersecting, co-dependent data since the act of scaling changes the nature of the intersections and the relationship between them. This may be shown by taking the possible value ranges for (3.47) and (3.48), calculated using (2.12), which are

$$\text{Eq. (3.47)} \Rightarrow (D_1 \cap D_2)|H_1 = \{1\} ,$$

$$(D_1 \cap D_2)|H_2 = \{0.5\} ,$$

$$\text{Eq. (3.48)} \Rightarrow (D_1 \cap D_2)|H_1 = \{0.0 \dots 0.5\} ,$$

$$(D_1 \cap D_2)|H_2 = \{0.0 \dots 0.25\} . \quad (3.49)$$

The effect of scaling has not only introduced uncertainty where previously there had been none, but has also introduced the possibility of 0 as a valid answer for both hypotheses. Further, the spatial distance between the hypotheses has also decreased. For these reasons it would seem unreasonable to assert that (3.47) and (3.48) share

the same likelihood ratio.

Using these principles and constraints it becomes possible to solve c_i . From the principle of symmetry it follows that

$$\begin{aligned} c_1(n, m, m, n) &= c_2(m, n, n, m) = c_2(n, m, m, n) , \\ c_1(n, m, n, m) &= c_2(n, m, n, m) = c_2(n, m, n, m) , \end{aligned} \quad (3.50)$$

and that the equalities (3.45), (3.46) for $P_i = 0.5$ automatically hold. Further, (3.44) solves to give

$$c_2(m, 1, n, 1) = \frac{2\sqrt{mn}c_1(m, 1, n, 1) - m + n}{2m\sqrt{n}} , \quad (3.51)$$

which, because $c_1(n, 1, m, 1) = c_2(m, 1, n, 1)$, finally gives

$$c_1(n, 1, m, 1) = \frac{2\sqrt{mn}c_1(m, 1, n, 1) - m + n}{2m\sqrt{n}} . \quad (3.52)$$

Substituting $g(m, n) := \sqrt{n}c_1(m, 1, n, 1)$ transforms (3.52) into an anti-symmetric bi-variate functional equation in m, n ,

$$g(m, n) - g(n, m) = \frac{m}{2\sqrt{mn}} - \frac{n}{2\sqrt{mn}} , \quad (3.53)$$

whose solution is $g(m, n) = \frac{m}{2\sqrt{mn}}$.

This gives a final solution for the coefficients $c_{1,2}$ of

$$\begin{aligned} c_1(x_1, y_1, x_2, y_2) &= \frac{\sqrt{x_1 y_1}}{2x_2 y_2} , \\ c_2(x_1, y_1, x_2, y_2) &= \frac{\sqrt{x_2 y_2}}{2x_1 y_1} . \end{aligned} \quad (3.54)$$

Thus, substituting (3.54) into (3.36) gives the likelihood ratio expression of,

$$P(H_1 | D_1 \cap D_2) = \frac{\frac{x_1 y_1}{x_2 y_2} + x_1 + y_1}{\frac{x_1 y_1}{x_2 y_2} + x_1 + y_1 + \frac{x_2 y_2}{x_1 y_1} + x_2 + y_2} . \quad (3.55)$$

Given that the population sizes of H_1 and H_2 are the same, no weighting of the elements needs to take place. Hence, the value of $P(H_1 | D_1 \cap D_2)$ for Figure 2.1 may

now be calculated to be

$$P(H_1|D_1 \cap D_2) \approx 0.5896 . \quad (3.56)$$

To return (3.55) to a quantum mechanical formalism, it is only necessary to include a parameter, in some form of \hbar , which, when going to 0, reproduces the classical result. Thus, for example, the solutions to (3.54) could be moderated as

$$\begin{aligned} c_1(x_1, y_1, x_2, y_2) &= \frac{\sqrt{x_1 y_1}}{2x_2 y_2} (1 - \exp(-\hbar)) , \\ c_2(x_1, y_1, x_2, y_2) &= \frac{\sqrt{x_2 y_2}}{2x_1 y_1} (1 - \exp(-\hbar)) , \end{aligned} \quad (3.57)$$

so that in the limit of $\hbar \rightarrow 0$, the intersection parameters, c_1 and c_2 , vanish to return the formalism to the classical situation of independent data.

3.6 A conjecture for a fully generalised quantum mechanical expression to calculate likelihood ratios from conditionally dependent data

The derivation of the expression (3.55) for a 2×2 contingency table would suggest that a similar derivation for the fully generalised case of m data and 2 hypotheses (H and \bar{H}) would be highly non-trivial. However, given the form of the 2×2 contingency table expression, it is possible to conjecture the structure of a fully generalised solution.

Assuming the complementarity of the hypotheses H_1 and H_2 , i.e.,

$$H_2 = \overline{H_1} , \quad (3.58)$$

and labelling the variables as

$$x_i := x_{i,1} , \quad \bar{x}_i := x_{i,2} ; \quad i = 1, 2, \dots, m , \quad (3.59)$$

gives the general contingency table (3.60).

	H_1	$H_2 = \overline{H_1}$
D_1	x_1	\bar{x}_1
D_2	x_2	\bar{x}_2
\vdots		\vdots
D_m	x_m	\bar{x}_m

(3.60)

From this the general solution (3.61) may be surmised.

$$P(H_1|D_1 \cap D_2 \cap \dots \cap D_m) = \frac{\sum_{i=1}^m x_i + \sum_{\sigma \in S_{\geq 2}} \frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i}}{\sum_{i=1}^m (x_i + \bar{x}_i) + \sum_{\sigma \in S_{\geq 2}} \left(\frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i} + \frac{\prod_{i \in \sigma} \bar{x}_i}{\prod_{i \in \sigma} x_i} \right)}, \quad (3.61)$$

where $P(H_1) = P(\overline{H_1})$.

For the case of non-even priors, it is necessary to scale the calculated probability for each hypothesis by its prior probability. Thus, the fully generalised expression becomes

$$P(H_1|D_1 \cap D_2 \cap \dots \cap D_m) = \frac{P(H_1) \frac{\sum_{i=1}^m x_i + \sum_{\sigma \in S_{\geq 2}} \frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i}}{\sum_{i=1}^m (x_i + \bar{x}_i) + \sum_{\sigma \in S_{\geq 2}} \left(\frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i} + \frac{\prod_{i \in \sigma} \bar{x}_i}{\prod_{i \in \sigma} x_i} \right)}}{P(H_1) \frac{\sum_{i=1}^m x_i + \sum_{\sigma \in S_{\geq 2}} \frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i}}{\sum_{i=1}^m (x_i + \bar{x}_i) + \sum_{\sigma \in S_{\geq 2}} \left(\frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i} + \frac{\prod_{i \in \sigma} \bar{x}_i}{\prod_{i \in \sigma} x_i} \right)} + P(\overline{H_1}) \frac{\sum_{i=1}^m \bar{x}_i + \sum_{\sigma \in S_{\geq 2}} \frac{\prod_{i \in \sigma} \bar{x}_i}{\prod_{i \in \sigma} x_i}}{\sum_{i=1}^m (x_i + \bar{x}_i) + \sum_{\sigma \in S_{\geq 2}} \left(\frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i} + \frac{\prod_{i \in \sigma} \bar{x}_i}{\prod_{i \in \sigma} x_i} \right)}}, \quad (3.62)$$

which simplifies to

$$P(H_1|D_1 \cap D_2 \cap \dots \cap D_m) = \frac{P(H_1) \left(\sum_{i=1}^m x_i + \sum_{\sigma \in S_{\geq 2}} \frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i} \right)}{P(H_1) \left(\sum_{i=1}^m x_i + \sum_{\sigma \in S_{\geq 2}} \frac{\prod_{i \in \sigma} x_i}{\prod_{i \in \sigma} \bar{x}_i} \right) + P(\overline{H_1}) \left(\sum_{i=1}^m \bar{x}_i + \sum_{\sigma \in S_{\geq 2}} \frac{\prod_{i \in \sigma} \bar{x}_i}{\prod_{i \in \sigma} x_i} \right)}. \quad (3.63)$$

3.6.1 Justification of (3.61)

$S_{\geq 2}$ is the index for all unordered subsets of $\{1, 2, 3, \dots, m\}$ with at least 2 elements. For instance, when $m = 2$, this would be $\{\{1, 2\}\}$. Equally, when $m = 3$, this would amount to $\{\{1, 2\}, \{1, 3\}, \{2, 3\}, \{1, 2, 3\}\}$. If $m = 4$, then the subsets would include all tuples from pairs up to quadruples.

Forming a monomial, by taking the product x_i over the indices, gives the element $\sigma \in S_{\geq 2}$, $\prod_{i \in \sigma} x_i$. For example, where $m=2$ there is only one element in $S_{\geq 2}$ which gives the monomial x_1x_2 . If $m = 3$, then the four elements of $S_{\geq 2}$ would generate the monomials x_1x_2 , x_1x_3 , x_2x_3 , and $x_1x_2x_3$ respectively.

Summing over all the monomial ratios, and adding all possible elements $\sigma \in S_{\geq 2}$, gives the expression (3.61) which may be seen to be both entirely consistent with, as well as an extrapolation of, (3.55).

3.6.2 An alternative expression of (3.61)

Although not a robust proof of (3.61), support for the correctness of this expression may be found by rewriting it in terms of standard elementary symmetric polynomials.

If

$$\begin{aligned}
 e_0(x_1, \dots, x_m) &= 1 , \\
 e_1(x_1, \dots, x_m) &= x_1 + x_2 + \dots + x_m , \\
 e_2(x_1, \dots, x_m) &= \sum_{1 \leq i \leq j \leq m} x_i x_j , \\
 e_3(x_1, \dots, x_m) &= \sum_{1 \leq i \leq j \leq k \leq m} x_i x_j x_k , \\
 &\dots \\
 e_m(x_1, \dots, x_m) &= x_1 x_2 \dots x_m ,
 \end{aligned} \tag{3.64}$$

then

$$\begin{aligned}
P(H_1|D_1 \cap D_2 \cap \dots \cap D_m) = & \\
& \frac{e_1(x_1, \dots, x_m) + \sum_{j=2}^m e_j(\alpha_1, \dots, \alpha_m)}{e_1(x_1 + \bar{x}_1, \dots, x_m + \bar{x}_m) + \sum_{j=2}^m e_j(\alpha_1, \dots, \alpha_m) + e_j(\frac{1}{\alpha_1}, \dots, \frac{1}{\alpha_m})}, \quad (3.65)
\end{aligned}$$

where $\alpha_{i=1, \dots, m} = \frac{x_i}{\bar{x}_i}$,

and $P(H_1) = P(\overline{H_1})$.

Checking (3.65) for consistency with all the limits and boundary conditions given in Section 3.5 demonstrates that:

1. The interchange of x and \bar{x} generates the expression for $P(\overline{H_1} | D_1 \cap D_2 \cap \dots \cap D_m)$.
From this the additivity of $P(H_1) + P(\overline{H_1})$ follows;
2. As demanded by probability theory, the result of (3.65) must fall between 0 and 1 since the numerator is a summand in the denominator;
3. When $x_i = \bar{x}_i$, i.e., the two columns of the contingency table are identical, then $\alpha_i = 1$ for all i in (3.65), giving $P(H_1|D_1 \cap D_2 \cap \dots \cap D_m) = 0.5$ as is required (3.66);

$$P(H_1|D_1 \cap D_2 \cap \dots \cap D_m) = \frac{e_1(x_1, \dots, x_m) + \sum_{j=2}^m e_j(1, \dots, 1)}{2e_1(x_1, \dots, x_m) + \sum_{j=2}^m 2e_j(1, \dots, 1)} = \frac{1}{2} \quad (3.66)$$

4. If any two rows are interchanged, then the answer remains the same since σ runs over all possible combinations of 2 or more indices from $\{1, 2, \dots, m\}$;
5. If the first row of the contingency table, i.e., D_1 , comprises (x_1, \bar{x}_1) , with all other rows set to $(1, 1)$, then $\alpha_1 = x_1/\bar{x}_1$ while all $\alpha_{i \geq 2} = 1$. Using the identity

expression (3.67), the numerator of (3.65) simplifies to (3.68) by subtracting out the first two terms for $j = 0, 1$ in $\sum_{j=0}^m$. (3.67) may be proven through the expansion of the product on the right-hand side of the expression.

$$\sum_{j=0}^m e_j(x_1, \dots, x_m) = \prod_{i=1}^m (1 + x_i) \quad (3.67)$$

$$e_1(x_1, \dots, x_m) + \prod_{i=1}^m (1 + \alpha_i) - 1 - e_1(\alpha_1, \dots, \alpha_m) \quad (3.68)$$

For the present case of $x_{i \geq 2} = \bar{x}_{i \geq 2} = \alpha_{i \geq 2} = 1$, this simplifies the numerator to (3.69).

$$x_1 + (m-1) + 2^{m-1}(1 + \alpha_1) - 1 - ((m-1) + \alpha_1) = x_1 + (2^{m-1} - 1)(\alpha_1 + 1) \quad (3.69)$$

After highly non-trivial cancellations in (3.70), the full expression for $P(H_1 | D_1 \cap D_2 \cap \dots \cap D_m)$ reduces, as expected, to (3.71).

$$\begin{aligned} P(H_1 | D_1 \cap D_2 \cap \dots \cap D_m) &= \\ &= \frac{x_1 + (2^{m-1} - 1)(\alpha_1 + 1)}{x_1 + (2^{m-1} - 1)(\alpha_1 + 1) + \bar{x}_1 + (2^{m-1} - 1)(\frac{1}{\alpha_1} + 1)} \\ &= \frac{x_1 + (2^{m-1} - 1)(\frac{x_1}{\bar{x}_1} + 1)}{x_1 + (2^{m-1} - 1)(\frac{x_1}{\bar{x}_1} + 1) + \bar{x}_1 + (2^{m-1} - 1)(\frac{\bar{x}_1}{x_1} + 1)} \end{aligned} \quad (3.70)$$

$$= \frac{x_1}{x_1 + \bar{x}_1} \quad (3.71)$$

3.7 Discussion

One of the greatest obstacles in developing any statistical approach is demonstrating correctness. This formula is no different in that respect. If correctness could be demonstrated then, a priori, there would be an appropriate existing method which would negate the need for a new one. All that may be hoped for in any approach is that it generates appropriate answers when they are known, reasonable answers for all other cases, and that these answers follow logically from the underlying mathematics.

However, what is clear is that the limitations of the naïve Bayes' classifier render any calculations derived from it open to an unknown margin of error. Given the importance of accurately deriving likelihood ratios this is troubling. This is especially true when these calculations are used to describe normative psychological theories from which inferences are drawn as to the failure of human logic (see, e.g., Doherty et al., 1979).

Yet, the question remains whether this “Quantum Bayes' Conjecture” handles the issue of conditional probabilities correctly. As measures of covariate overlap, the c_{ij}^α inner products, defined in (3.24), are arguably the pure representations of the conditionalised probabilities that exist between any two ordinal data, for a given hypothesis, within a contingency table. However, the solution to these antisymmetric functional equations relies upon inference from a series of boundary conditions, as well as the underlying ordinal data from the contingency table. As such, it is possible to conclude that the Quantum Bayes' Conjecture, as presented, is not a true measure of conditionally dependent probability. Such an assertion would not be correct. Given that the effects of conditional dependence between data are unknown, the only reasonable, logical conclusion is that the best estimate of probability must come from an average of the data and the linear combination of all possible ratios that exist within the contingency table. In this way, probability may be seen to emanate from the contingency table as an integrated statistical system rather than from discrete ordinal data. Indeed, assuming conditional independence, as with the naïve Bayes' classifier, is not statistically neutral. For the example contingency table presented in Figure 2.1, all the data take values > 0.5 . As a consequence, an aversive conditional relationship between the data has a greater potential effect on the calculated p -value than a positive relationship. Thus, it is dangerous to presume that an assumption of conditional independence provides some sort of “neutral”, middle path.

For these reasons, the normativity of the Quantum Bayes' Conjecture as the best measure of likelihood for conditionally dependent data is asserted.

3.8 Conclusion

This chapter has demonstrated both theoretically, and practically, that a quantum mechanical methodology can overcome the axiomatic limitations of classical statistics in respect to their application within cognitive psychology. In doing so, it challenges the orthodoxy of de Finetti’s epistemological approach to statistics by demonstrating that it is possible to derive “real” likelihood ratios from information systems without recourse to arbitrary and subjective evaluations.

As a quantum mechanical methodology this Quantum Bayes’ Conjecture is able to calculate accurate, iteration free, likelihood ratios which fall beyond the scope of existing statistical techniques, and offers a new theoretical approach within cognitive psychology. Further, with the addition of a Hamiltonian operator to introduce time-evolution, this expression could offer likelihood ratios for future system states with appropriate updating of the contingency table. In contrast, Bayes’ theorem is unable to distinguish directly between time-dependent and time-independent systems. This may lead to situations where the process of contingency table updating results in the same decisions being made repeatedly with the appearance of an ever increasing degree of certainty. Indeed, from (3.21), it would seem that the naïve Bayes’ classifier is only a special case of a more complex quantum mechanical framework, and may only be used where the conditional independence of data is guaranteed.

Chapter 4

On the estimation of probability

4.1 Introduction

The notable feature of the Quantum Bayes' Conjecture, presented in Chapter 3, is that it derives a probability estimate by combining and averaging the ratios that exist within a contingency table. Thus, the question arises as to whether, when making probability estimations, people use knowledge of statistical relationships in a similar fashion to the way they make ordinal decisions, as described in Chapter 2.

The following experiment duplicates the structure of those presented in Chapter 2. By requiring participants to select data and make estimates of likelihood under uncertainty, it is possible to not only test for any differences in modelling power of the naïve Bayes' classifier and the Quantum Bayes' Conjecture, but also determine whether the results are consistent with the notion that people apply estimates for missing data. Further support for the idea that people estimate unknown values may also come by presenting questions using all three contingency table sizes tested in Chapter 2, i.e., 2×2 , 2×4 , and 3×4 contingency tables. Here, the increase in contingency table size, and associated uncertainty, should be reflected by a wider variation in participant responses.

Existing claims of base-rate neglect (see, e.g., Kahneman and Tversky, 1973; Doherty et al., 1979) may also be considered. Adopting the simple approach of using the naïve Bayes' classifier and the Quantum Bayes' Conjecture to calculate likelihoods

both with and without the inclusion of prior probabilities, linear regression analysis should indicate which approach is most consistent with participant estimates. In the event that only the naïve Bayes' classifier demonstrates support for base-rate neglect, then the effect might be argued to be a Type-I error resulting from the use of non-normative mathematics. Such a finding would also raise questions regarding Kahneman and Tversky's assertion that it is the ignoring of base-rates which leads to the over-estimation of extreme events.

4.2 Research questions

RQ1

Is there evidence that people generally apply either the naïve Bayes' classifier or the Quantum Bayes' Conjecture when estimating probability?

RQ2

Are people's estimations of likelihood consistent with the use of estimates for unknown data?

RQ3

Is there evidence for base-rate neglect, or the over-estimation of extreme events?

4.3 Experiment

4.3.1 Participants

The participants ($n = 175$) were recruited through social media networks. The results comprise those of the first 175 participants who completed the experimental exercises. There were no exclusions and there was no inducement to participate.

4.3.2 Design, materials, and procedure

Using a publicly accessible online experimental format, participants were presented with three decision-making tasks constructed using two hypotheses with two diagnostic criteria, two hypotheses with four diagnostic criteria, and three hypotheses with four diagnostic criteria. The questions asked were randomly selected from the set of six questions in Appendix B.2, but may be summarised as:

1. Determining the make of a friends' car;
2. Deciding to which political group a Member of the European Parliament belongs;
3. Determining from which of two nearby islands an archaeological find is most likely to have originated (after Doherty et al.);
4. Deciding with which mobile phone operator to take out a contract;
5. Deciding where to go on holiday;
6. Determining which electricity supplier to recommend to readers of a magazine.

No question could be asked of the same participant twice, and presentation order of the three tasks was randomised. In all cases the prior, “base-rate” information, as well as one piece of diagnostic information from the first diagnostic criteria, was provided. This “anchor” information was randomly allocated to one of the hypotheses. The participants were instructed to reveal more data before making a probability estimate, such that only 50% of the contingency information for each exercise would be known. The estimation was given using a drop down selection menu which provided all possible probabilities from 1–100% in 5% increments. All the prior and posterior information was randomly generated using the API at www.random.org. The naïve Bayes' classifier and Quantum Bayes' Conjecture calculations of $P(H_1|D_1, \dots, D_x)$, based on participant data selections, as well as participant estimates of p and the error sizes, may be found in Appendix E. Unknown data were presumed to take values of 0.5.

4.3.3 Results

Linear regressions & Paired t-tests

Linear regressions of the results for the 2×2 , 2×4 , and 3×4 contingency tables suggest that the Quantum Bayes' Conjecture estimates for $P(H_1|D_1, \dots, D_x)$ consistently model participant estimations of $P(H_1|D_1, \dots, D_x)$ more accurately than the standard naïve Bayes' classifier (Figures 4.2–4.10). However, although the correlations are moderate, given the inevitable closeness of both the quantum and naïve classifier estimations, the difference between the r^2 values for each contingency table case are not significant. There also appears to be an increase in the variation of participant estimations with increased contingency table size. The regression results may be found in Tables 4.1–4.3. Note that the analysis of the 3×4 contingency table is based on the concatenation of H_2 and H_3 to form a unified $\overline{H_1}$.

Given that the difference in r^2 values for each contingency table regression are unlikely ever to be significant, an alternative analytical approach is to compare the errors between participant estimates for $P(H_1|D_1, \dots, D_x)$ and the calculated values using both the naïve Bayes' classifier and Quantum Bayes' Conjecture.

For the 2×2 contingency table there is a difference in the participant estimate errors generated by the naïve Bayes' classifier and Quantum Bayes' Conjecture which is significant: $t = -1.9783$, $df = 174$, $CI = 95\% [-0.00986, -0.00001]$, $p = 0.0495$ (two-tailed). The distribution shape of the two data sets is essentially the same, with the Kolmogorov-Smirnov test giving $KS = 0.04$, and $p = 0.999$. This is consistent with the standard deviations where $SD(\text{Participant estimate} - \text{Naïve Bayes' classifier estimate}) = 0.2619$, and $SD(\text{Participant estimate} - \text{Quantum Bayes' Conjecture estimate}) = 0.2598$. The mean error given by Participant estimate – Naïve Bayes' classifier estimate is $\mu = -0.0111$. For Participant estimate – Quantum Bayes' Conjecture estimate, the mean error nearly halves with $\mu = -0.0062$.

For the 2×4 and the 3×4 contingency tables, the calculated t-test p fails to reach significance. With the 2×4 contingency table, the calculated p drifts away from significance: $t = 1.4716$, $df = 149$, $CI = 95\% [-0.000798, 0.00542]$, $SD(\text{Participant$

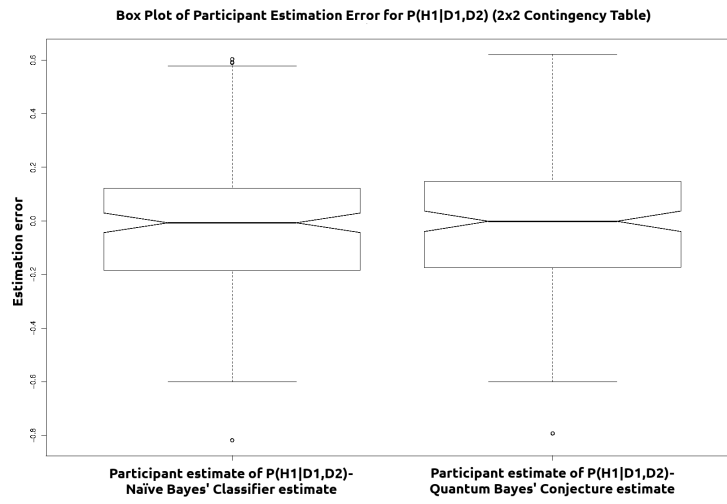


Figure 4.1: Box plot of participant estimation error of $P(H_1|D_1, D_2)$ for a 2×2 contingency table

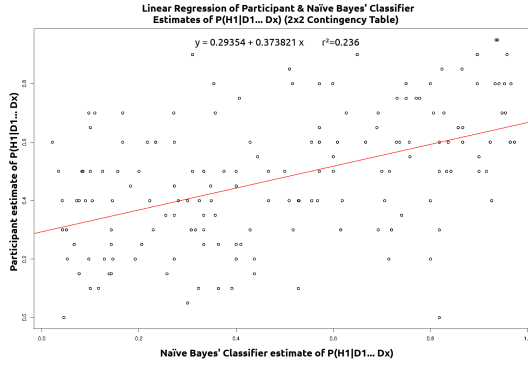
Table 4.1: Statistics for regressions of participant estimates of $P(H_1|D_1, D_2)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table

(a) Statistics for regression of Naïve Bayes' Classifier & participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table

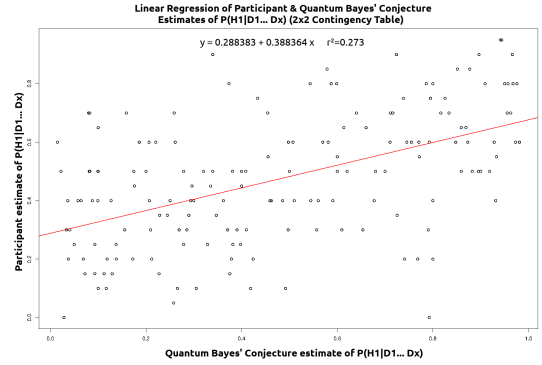
Parameter	Value	S.E.	T-Stat
Constant	0.294	0.029	10.191
Slope	0.374	0.051	7.312
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	1.975	1.975
Residuals	173	6.390	0.037
Total	174	8.365	
F-test	53.469		

(b) Statistics for regression of Quantum Bayes' Conjecture & participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table

Parameter	Value	S.E.	T-Stat
Constant	0.288	0.027	10.604
Slope	0.388	0.048	8.059
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	2.283	2.283
Residuals	173	6.082	0.035
Total	174	8.365	
F-Test	64.945		

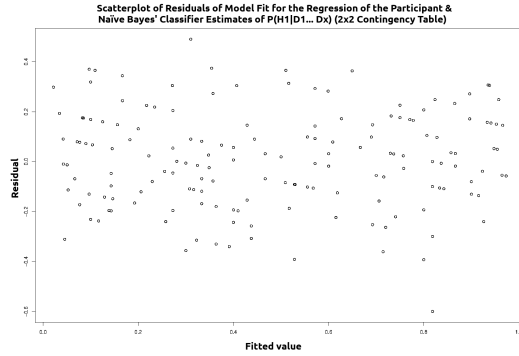


(a) Regression of Naïve Bayes' Classifier and participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table ($r^2 = 0.236$)

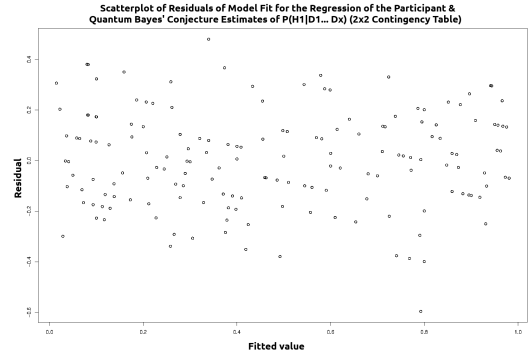


(b) Regression of Quantum Bayes' Conjecture and participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table ($r^2 = 0.273$)

Figure 4.2: Regressions of participant estimates of $P(H_1|D_1, D_2)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table

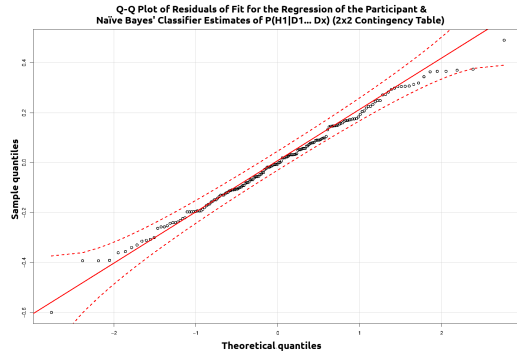


(a) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier estimates for a 2×2 contingency table

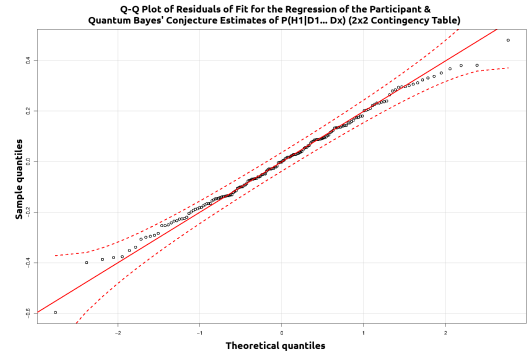


(b) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, D_2)$ against the Quantum Bayes' Conjecture estimates for a 2×2 contingency table

Figure 4.3: Scatter plots of residuals of model fit for the regressions of participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table



(a) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier estimates for a 2×2 contingency table



(b) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, D_2)$ against the Quantum Bayes' Conjecture estimates for a 2×2 contingency table

Figure 4.4: Q-Q plots of residuals of fit for the regressions of the participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table

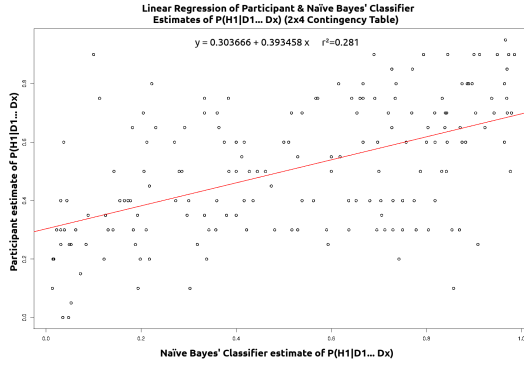
Table 4.2: Statistics for regressions of participant estimates of $P(H_1|D_1, \dots, D_4)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×4 contingency table

(a) Statistics for regression of Naïve Bayes' Classifier & participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 2×4 contingency table

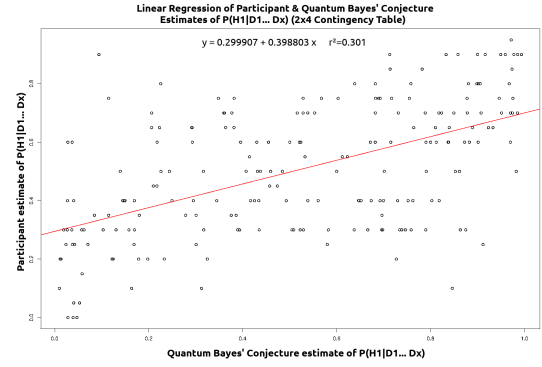
Parameter	Value	S.E.	T-Stat
Constant	0.304	0.029	10.573
Slope	0.393	0.048	8.225
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	2.418	2.148
Residuals	173	6.184	0.036
Total	174	8.602	
F-Test	67.657		

(b) Statistics for regression of Quantum Bayes' Conjecture & participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 2×4 contingency table

Parameter	Value	S.E.	T-Stat
Constant	0.300	0.028	10.720
Slope	0.399	0.046	8.633
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	2.590	2.590
Residuals	173	6.012	0.035
Total	174	8.602	
F-Test	74.533		

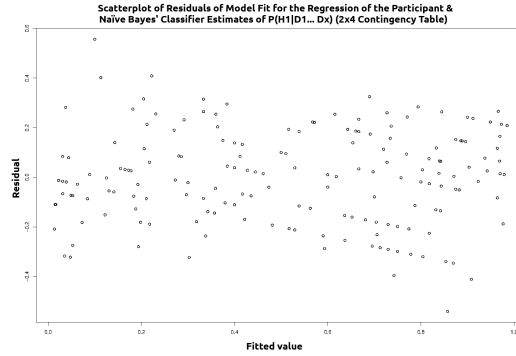


(a) Regression of Naïve Bayes' Classifier and participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 2×4 contingency table ($r^2 = 0.281$)

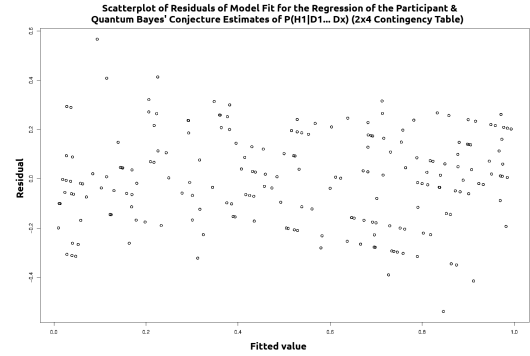


(b) Regression of Quantum Bayes' Conjecture and participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 2×4 contingency table ($r^2 = 0.301$)

Figure 4.5: Regressions of participant estimates of $P(H_1|D_1, \dots, D_4)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×4 contingency table

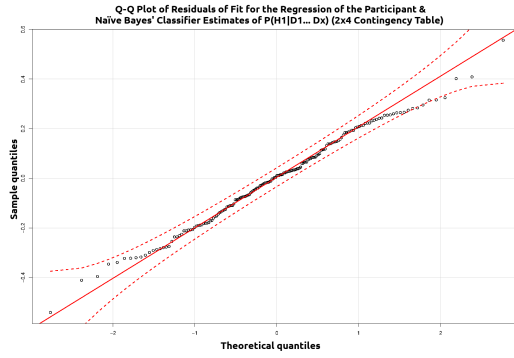


(a) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier estimates for a 2×4 contingency table

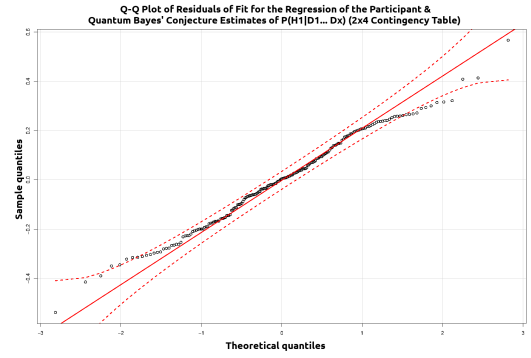


(b) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Quantum Bayes' Conjecture estimates for a 2×4 contingency table

Figure 4.6: Scatter plots of residuals of model fit for the regressions of participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×4 contingency table



(a) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier estimates for a 2×4 contingency table



(b) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Quantum Bayes' Conjecture estimates for a 2×4 contingency table

Figure 4.7: Q-Q plots of residuals of fit for the regressions of the participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×4 contingency table

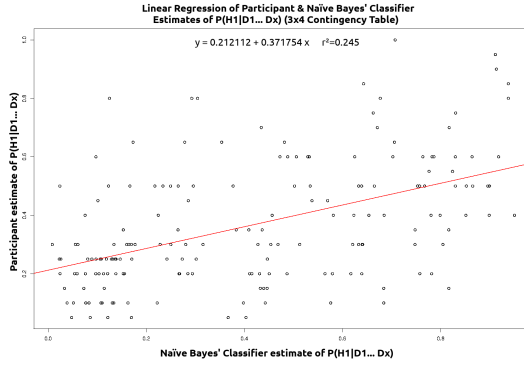
Table 4.3: Statistics for regressions of participant estimates of $P(H_1|D_1, \dots, D_4)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 3×4 contingency table (Note: H_2 and H_3 have been concatenated to form a unified $\overline{H_1}$)

(a) Statistics for regression of Naïve Bayes' Classifier & participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 3×4 contingency table

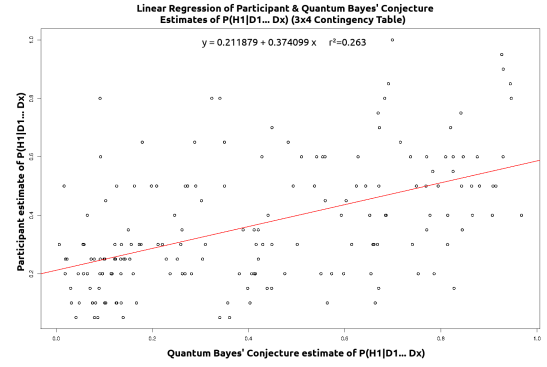
Parameter	Value	S.E.	T-Stat
Constant	0.212	0.025	8.535
Slope	0.372	0.050	7.500
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	1.904	1.904
Residuals	173	5.857	0.034
Total	174	7.761	
F-Test	56.248		

(b) Statistics for regression of Quantum Bayes' Conjecture & participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 3×4 contingency table

Parameter	Value	S.E.	T-Stat
Constant	0.212	0.024	8.831
Slope	0.374	0.048	7.865
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	2.044	2.044
Residuals	173	5.717	0.033
Total	174	7.761	
F-Test	61.862		

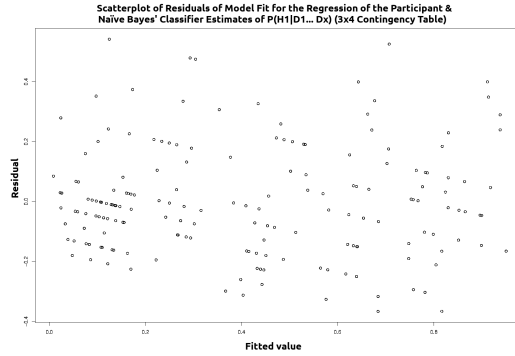


(a) Regression of Naïve Bayes' Classifier and participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 3×4 contingency table ($r^2 = 0.245$)

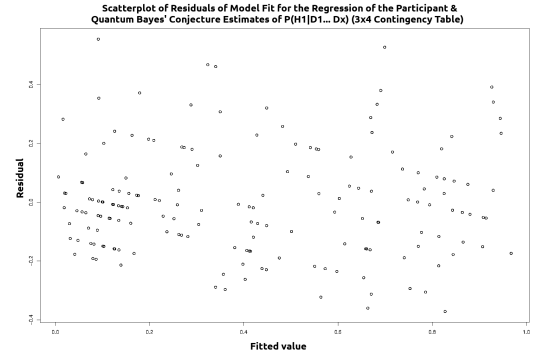


(b) Regression of Quantum Bayes' Conjecture and participant estimates of $P(H_1|D_1, \dots, D_4)$ for a 3×4 contingency table ($r^2 = 0.263$)

Figure 4.8: Regressions of participant estimates of $P(H_1|D_1, \dots, D_4)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 3×4 contingency table

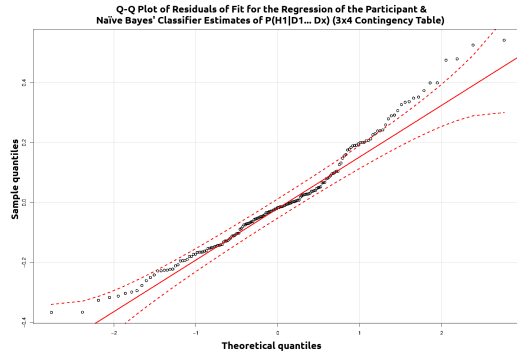


(a) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier estimates for a 3×4 contingency table

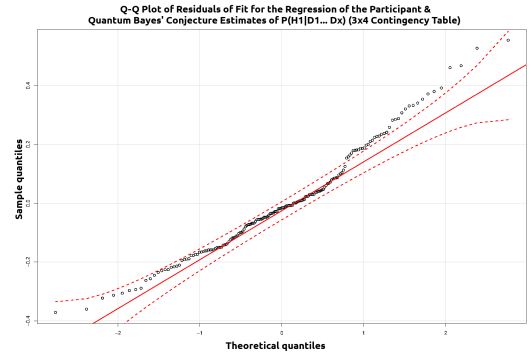


(b) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Quantum Bayes' Conjecture estimates for a 3×4 contingency table

Figure 4.9: Scatter plots of residuals of model fit for the regressions of participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 3×4 contingency table



(a) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier estimates for a 3×4 contingency table



(b) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Quantum Bayes' Conjecture estimates for a 3×4 contingency table

Figure 4.10: Q-Q plots of residuals of fit for the regressions of the participant estimates of $P(H_1|D_1, \dots, D_4)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 3×4 contingency table

estimate – Naïve Bayes’ classifier estimate) = 0.25233, and $SD(\text{Participant estimate} - \text{Quantum Bayes’ Conjecture estimate}) = 0.2518$, $p = 0.1432$ (two tailed). While for the 3×4 contingency table, the result is highly non-significant: $t = 0.5053$, $df = 149$, $CI = 95\% [-0.000216, 0.00365]$, $SD(\text{Participant estimate} - \text{Naïve Bayes’ classifier estimate}) = 0.2655$, and $SD(\text{Participant estimate} - \text{Quantum Bayes’ Conjecture estimate}) = 0.26712$, $p = 0.6141$ (two tailed). Note that the analysis of the 3×4 contingency table is based on the concatenation of $P(H_2)$ and $P(H_3)$ to form a unified $P(\bar{H}_1)$.

These results indicate that, for the 2×2 contingency table, the Quantum Bayes’ Conjecture is a significantly better predictor of participant estimation of probability than the naïve Bayes’ classifier.

Base-rate neglect

Regression analysis of the 2×2 contingency table results demonstrate that if the base-rate data is ignored then the correlation between the naïve Bayes’ classifier and participant estimates of $P(H_1|D_1, D_2)$ improves markedly from $r^2 = 0.236$ to $r^2 = 0.284$ (see Tables 4.1(a); 4.4(a), and Figures 4.2(a); 4.11(a)). This finding is entirely consistent with previous literature. However, the case for base-rate neglect is far less clear when participant estimates of $P(H_1|D_1, D_2)$ are modelled against the Quantum Bayes’ Conjecture. Although the value of r^2 increases marginally with base-rate neglect, from $r^2 = 0.273$ to $r^2 = 0.295$ (see Tables 4.2(b); 4.4(b), and Figures 4.2(b); 4.11(b)), the introduction of marked deviations of the central points from the linear fit line in the Q-Q residuals plot with base-rate neglect are indicative of a loss of modelling power (see Figures 4.4(b); 4.13(b)).

The estimation of missing data

While the principle of estimating missing data within the Bayesian framework is contentious, the Quantum Bayes’ Conjecture’s use of ratios demands that estimations are made. That the estimations made by the Quantum Bayes’ Conjecture

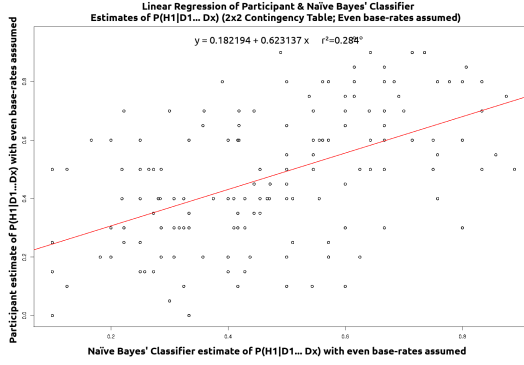
Table 4.4: Statistics for regressions of participant estimates of $P(H_1|D_1, D_2)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table (Even base-rates assumed)

(a) Statistics for regression of Naïve Bayes' Classifier & participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table (Even base-rates assumed)

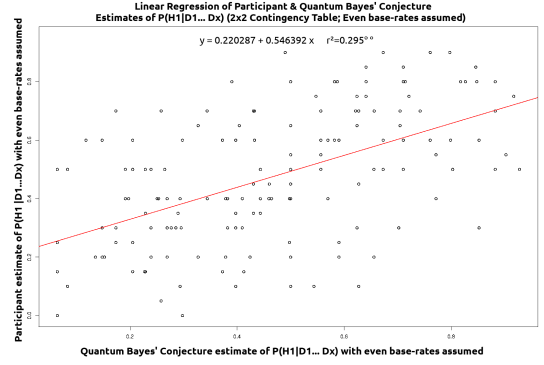
Parameter	Value	S.E.	T-Stat
Constant	0.182	0.038	4.782
Slope	0.623	0.075	8.282
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	2.375	2.375
Residuals	173	5.990	0.035
Total	174	8.365	
F-test	68.592		

(b) Statistics for regression of Quantum Bayes' Conjecture & participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table (Even base-rates assumed)

Parameter	Value	S.E.	T-Stat
Constant	0.220	0.033	6.659
Slope	0.546	0.064	8.507
ANOVA	DF	Sum of Squares	Mean Square
Regression	1	2.467	2.467
Residuals	173	5.898	0.034
Total	174	8.365	
F-Test	72.364		

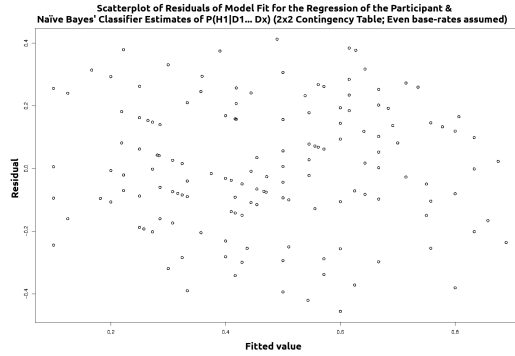


(a) Regression of Naïve Bayes' Classifier and participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table ($r^2 = 0.284$) (Even base-rates assumed)

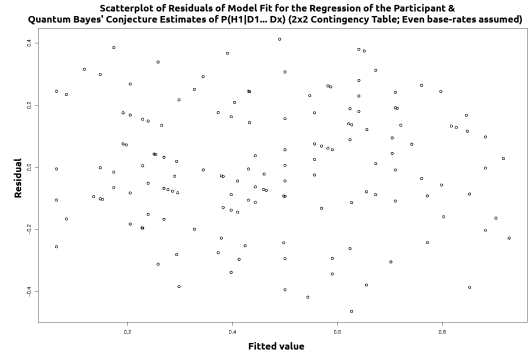


(b) Regression of Quantum Bayes' Conjecture and participant estimates of $P(H_1|D_1, D_2)$ for a 2×2 contingency table ($r^2 = 0.295$) (Even base-rates assumed)

Figure 4.11: Regressions of participant estimates of $P(H_1|D_1, D_2)$ against Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table (Even base-rates assumed)

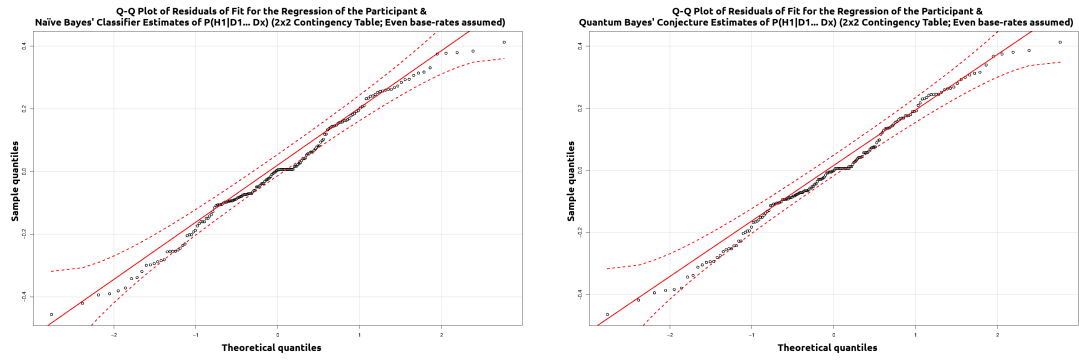


(a) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier estimates for a 2×2 contingency table (Even base-rates assumed)



(b) Scatter plot of residuals of model fit for the regression of participant estimates of $P(H_1|D_1, D_2)$ against the Quantum Bayes' Conjecture estimates for a 2×2 contingency table (Even base-rates assumed)

Figure 4.12: Scatter plots of residuals of model fit for the regressions of participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table (Even base-rates assumed)



(a) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier estimates for a 2×2 contingency table (Even base-rates assumed)

(b) Q-Q plot of residuals of fit for the regression of the participant estimates of $P(H_1|D_1, D_2)$ against the Quantum Bayes' Conjecture estimates for a 2×2 contingency table (Even base-rates assumed)

Figure 4.13: Q-Q plots of residuals of fit for the regressions of the participant estimates of $P(H_1|D_1, D_2)$ against the Naïve Bayes' Classifier & Quantum Bayes' Conjecture estimates for a 2×2 contingency table (Even base-rates assumed)

consistently model participant estimates of $P(H_1|D_1, \dots, D_x)$ more successfully than the naïve Bayes' classifier suggests that people use estimates for unknowns in their decision-making process. Further, the increased variation in participant estimates with contingency table size, noted visually in Figures 4.2, 4.5, and 4.8, and confirmed by the reduced t-test significance of the Quantum Bayes' Conjecture over the naïve Bayes' classifier, is also consistent with the increased uncertainty associated with a higher number of estimated data. This assertion is further supported by the broadly consistent correlations for the 2×2 , 2×4 , and 3×4 contingency tables, at $r^2 = 0.273$, $r^2 = 0.301$, and $r^2 = 0.263$, which demonstrate that the extra variation in participant estimates is, more or less, evenly distributed over the sample space.

The conditional dependence of hypotheses

The Bland-Altman plots (Figure 4.14) would appear to show a clear relationship between the over-estimation of likelihood for low probability outcomes and an under-estimation of likelihood for high probability outcomes. This suggests that there is an aversion to the prediction of extreme events, with estimates of probability being moderated to more central figures. This interpretation is consistent with the deviations of the extreme points from the fit line observed in the correlation Q-Q residual plots (see Figures 4.4(b), 4.7(b), and 4.10(b)). Whether this moderation occurs as a post-hoc phenomenon, or during the estimation of missing data, is unclear. In the latter case, however, logical consistency would imply that in their assessment of contingency data the participants presumed a conditional dependence between the hypotheses even though they were mutually exclusive. This is consistent with the principles of Relational Information Theory.

4.4 Discussion

The results of this experiment show that, across all contingency table sizes, the Quantum Bayes' Conjecture provides a better model of participant estimates of $P(H_1|D_1, \dots, D_x)$ than the naïve Bayes' classifier. Further, as a predictor of participant estimates the Quantum Bayes' Conjecture is significantly better than the naïve Bayes' classifier for a 2×2 contingency table. Although a certain degree of

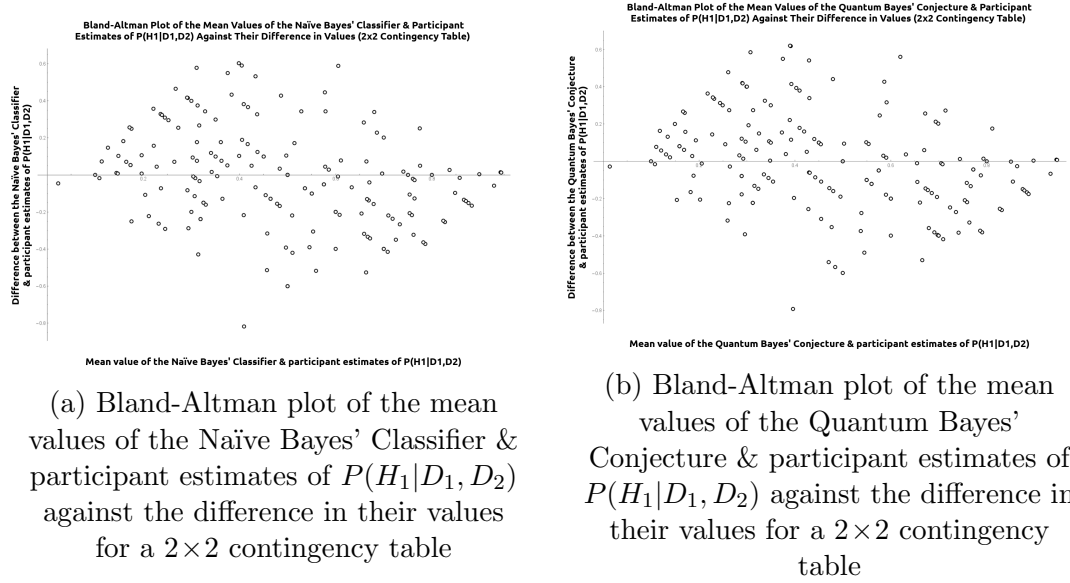


Figure 4.14: Bland-Altman plots of the mean values of the Naïve Bayes' Classifier & participant estimates of $P(H_1|D_1, D_2)$, and the Quantum Bayes' Conjecture & participant estimates of $P(H_1|D_1, D_2)$, against the difference in their values for a 2×2 contingency table

circumspection must be shown when interpreting these results, especially given the variability of the t-test analyses for estimation error, the improvement in modelling power of the Quantum Bayes Conjecture, over the the naive Bayes classifier, does suggest a participant propensity to average probabilities over the contingency table space, rather than to assume the conditional independence of the posterior data. Indeed, the loss of significance for error estimation in the 2×4 and 3×4 contingency tables would appear to be at odds with the results obtained from the regression analyses.

The Quantum Bayes' Conjecture results raise questions about the strength of the base-rate neglect phenomenon. Although an improved correlation model was observed by ignoring prior probabilities with the naïve Bayes' classifier, this was not as marked with the Quantum Bayes' Conjecture.

The Bland-Altman “mean vs. difference” plots (Figure 4.14) seem to show that when the average of the calculated p-value and the participant estimate is low, then the difference between the estimates is a positive value. Conversely, when the average value of the calculated and participant estimates is high, then the difference

between the estimates becomes a negative value. This result would seem only to be consistent with participants moderating their estimates towards a mean, $p=0.5$, value.

While these results are compelling, they also appear to oppose received wisdom in many areas of decision-making theory. Doherty et al. premised their claim that the pseudodiagnosticity paradigm shows “cognitively dysfunctional” behaviour upon the assumption that the naive Bayes’ classifier is normative and, hence, that any estimation of missing data values leads to inconsistent results. As a symmetrical expression, however, the Quantum Bayes’ Conjecture not only requires estimates of missing data values, but also remains unaffected by their presence. That the Quantum Bayes’ Conjecture estimates more closely model the participants’ estimates of likelihood than the naive Bayes’ classifier suggests that not only are estimations for unknown values made but, also, that rather than being dysfunctional they are rational when there is no assertion of conditionally independent posterior data.

4.5 Conclusion

The results of the experiment, described in this chapter, demonstrate that the Quantum Bayes’ Conjecture developed in Chapter 3 represents a better model of people’s estimation of probability than the naïve Bayes’ classifier. This is not to suggest that people think in a “quantum” way, only that the classical solution to the Quantum Bayes Conjecture represents an intuitive way to assess likelihood under uncertainty. However, as a predictive model, this research does raise questions about many aspects of existing decision-making theory. In particular, this new framework finds little evidence to support ideas such as “base-rate neglect”, “confirmation bias”, the over-estimation of extreme events, or general failings in participant logic. Further, where the value of making estimations for unknown data is contentious when applying the naïve Bayes’ classifier, estimations are fundamental to the Quantum Bayes’ Conjecture due to its symmetry. That the Quantum Bayes’ Conjecture provides a better model of how people estimate probability strongly sug-

gests such estimations are made. This is consistent with the idea behind Relational Information Theory that decision-making is based on the development of integrated mental models of statistical systems.

Chapter 5

Conclusion

This thesis has considered the twin issues of ordinal decision-making under uncertainty and likelihood estimation. From this, a theory of “Relational Information” has been proposed which emphasises the mathematical value of the relationships between data rather than their discrete values.

Chapter 2 considered the claims of “pseudodiagnosticity” made by Doherty et al. (1979) which resulted from their research into base-rate neglect. By challenging the received wisdom that making ordinal decisions relies upon a precise calculation of likelihood, Chapter 2 shows the efficacy of a decision-making approach based on knowledge of overall data structure. Here, data selection follows a heuristically-based, entropy driven pattern where a final selection of the weakest information-theoretic data uses set theory to investigate the possibility of any structural bias which might affect likelihood estimation.

The ethos of these research findings is consistent with Gigerenzer and Goldstein (1996). Indeed, the starting point for both their paper and this research is a computational model which shows that a heuristic algorithm may outperform allegedly normative, mathematically based, deductive logical systems. Further, both Gigerenzer and Goldstein, and Chapter 2, also provide evidence that participants use these heuristic methods within their respective experimental paradigms. Unlike Gigerenzer and Goldstein, however, Chapter 2 does not concern itself with the decisions that participants reach, only the choice of data which underpin any decision. While,

in part, this results from paradigmatic differences between the respective research methodologies, it is also the result of the need to separate the mechanical process of decision-making from the final decision itself. This is because it is unreasonable to assert logical failure on the grounds of an incorrect decision, given optimal data selection, since it is impossible to disambiguate the effect of any lack of mathematical knowledge.

In helping to establish that heuristic processes may also be mathematically optimal, Chapter 2 builds a bridge between normative and descriptive decision-making theories. While Gigerenzer and Hoffrage (1995) proposed that people use short-cut heuristics to simplify Bayesian reasoning problems, the Relational Information Theory strategy shows not only the effectiveness of such an approach but also its use, with contingency data understood as a complete system with internal statistical relationships. In doing so, this strategy questions the findings of confirmation bias in pseudodiagnosticity tasks. If people build mental representations of mathematical structures on the basis of their heuristic assessment of entropy, then any apparent confirmation bias would seem to be little more than an analytical error due to the misidentification of the motivations underpinning search patterns. With the Relational Information Theory strategy there is no hypothesis generation, confirmation, or refutation. Rather, there is only a process of data acquisition to aid model building which leads to a decision.

However, the Relational Information Theory strategy, as presented in Chapter 2, is premised on the idea that ordinal decisions may be reached heuristically and without recourse to a precise calculation of probability. The question arises, therefore, as to how the likelihood of events is assessed when a precise probability is demanded. Chapter 3 highlighted the limitations of the naïve Bayes' classifier as a normative expression for the estimation of likelihood, given its underlying assumption of the conditional independence of contingency data, and developed an alternative expression for the calculation of probability derived from the mathematics of quantum mechanics. In doing so, Chapter 3 presented the Quantum Bayes' Conjecture that reconceptualises probabilistic information systems as isomorphic

representations of quantised and entangled systems. It is asserted that only such an approach allows for probability calculations which are largely free from underlying mathematical assumptions, and proposes that the estimation of likelihood depends upon the relationships that exist between ordinal data, as expressed in terms of polynomials. The results of an experiment, described in Chapter 4, suggest that the Quantum Bayes' Conjecture is both a better model of, and a significantly better predictor of, participant estimations of probability than the naïve Bayes' classifier.

Yet, there are objections to the idea that probability estimation uses a holistic knowledge of statistical relationships. For instance, Kahneman and Tversky (1973) have suggested that heuristics, e.g., representativeness, affect event prediction and lead to statistical information such as base-rates, or priors, being ignored in favour of belief. A consequence of this is the over-estimation of likelihood for extreme events. However, such research has concentrated upon questions which assume prior knowledge. With artificially constructed questions, such as that used by Doherty et al. and those used in Chapter 2, there can be no relevant prior knowledge. As such, these questions may offer a purer measure of the essential nature of human decision-making under uncertainty, largely unencumbered by perceptions of "how the world works". The apparent moderation of extreme estimated p-values, found in the research reported in Chapter 4, suggest that it is only the probability of unlikely events which are over-estimated. Yet, this result is not necessarily inconsistent with the work of Kahneman and Tversky. The premise behind both the Quantum Bayes' Conjecture, and Relational Information Theory, is that the cognitive processes involved in decision-making are directed towards establishing how pieces of knowledge relate to each other. With ecologically valid questions, it might be that participants establish relationships not just between presented data, but also with prior knowledge. There is no mathematical reason not to extend the Quantum Bayes' Conjecture to include this knowledge through extra initial vectors, inner products, and boundary conditions. Indeed, this would provide a richer approach to including belief in decision-making than the blunt-force approach of prior manipulation required by the naïve Bayes' classifier. However, such an extension to the Quantum Bayes' Conjecture would suggest that while Kahneman and Tversky's

observation of a biasing effect may be correct, their conclusion of base-rate neglect is not. Rather, pre-existing knowledge might integrate into a complete model of the decision problem in such a way that the cognitive “certainties” of belief receive an undue weighting compared to the presented “uncertain” data.

Whether decision-making is heuristically driven, or dependent upon a calculation of likelihood, the research presented in this thesis clearly demonstrates the importance of inter-data relationships in cognition. As such, Relational Information Theory is consistent with the principle of mental model construction posited by Johnson-Laird (1983). However, unlike Johnson-Laird (2010), Relational Information Theory does not require the creation, and comparison, of separate mental models for every possible outcome. Instead, the decision-making conclusion is seen to emanate naturally from an understanding of the internal relationships within a statistical system. In this there is, therefore, a similarity with the mental-logic work of Braine and O’Brien (1991) who argue that conclusions are inferred from a set of propositions. If statistical relationships are considered as a set of logical propositions, then it follows that Relational Information Theory helps bridge the disparate perspectives of “information gain” (Oaksford and Chater, 1994, 1995), mental models (Johnson-Laird, 1983), heuristics (Gigerenzer and Goldstein, 1996; Kahneman and Tversky, 1973), and semantically driven decision-making (Braine and O’Brien, 1991).

In conclusion, Relational Information Theory demonstrates the importance of the relationships between probabilistic data in decision-making theory. Further, in developing the Quantum Bayes’ Conjecture, this thesis show not only the appropriateness of quantum-mechanical modelling in Psychology, but also how such an approach can improve on existing, classically derived models as descriptions of cognition. In doing so, this research represents a way forward to unifying the normative and descriptive approaches of decision-making theory.

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Appendix A

Modelling code

A.1 Modelling code for Table 2.1

```
<?php

/* *****
/*
/* This code iterates through all prior and posterior
/* data for a 2x2 contingency table in 0.1 increments,
/* and calculates for each of 4 selection strategies
/* which gives the closest estimate to the actual
/* naive Bayes' classifier probability.
/*
/* *****

// PHP/Zend framework for ease and portability

// Initialise arrays and strings
$ColumnCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$ColumnWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$RowCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$RowWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$DiagonalCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$DiagonalWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$CrupiCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$CrupiWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$CrupiTries = array(0,0,0,0,0,0,0,0,0,0,0);
$BaseRateTries = array(0,0,0,0,0,0,0,0,0,0,0);
$AvBayesEstimate = array(0,0,0,0,0,0,0,0,0,0,0);
$AvRowEstimate = array(0,0,0,0,0,0,0,0,0,0,0);
$AvColumnEstimate = array(0,0,0,0,0,0,0,0,0,0,0);
$AvCrupiEstimate = array(0,0,0,0,0,0,0,0,0,0,0);
$TotalRowCorrect = '0';
$TotalRowWrong = '0';
$TotalColumnCorrect = '0';
$TotalColumnWrong = '0';
$TotalDiagonalCorrect = '0';
$TotalDiagonalWrong = '0';
```

```

$TotalCrupiCorrect = '0';
$TotalCrupiWrong = '0';
$TotalCrupiTries = '0';
$TotalTries = '0';
$TotalBayesEstimate = '0';
$TotalRowEstimate = '0';
$TotalColumnEstimate = '0';
$TotalCrupiEstimate = '0';
$Buffer1 = '0';
$Buffer2 = '0';
$Output = '';

$BR1 = '0';
$BR2 = '1';
$Loop1and3 = '0';
$Loop2and4 = '100';

// Start the loop to iterate through the base rates
for ($iteration='1'; $iteration<='9'; $iteration++) {

$BR1 = $BR1+0.1;
$BR2 = $BR2-0.1;
$Loop1and3 = $Loop1and3+10;
$Loop2and4 = $Loop2and4-10;

// Start the loops to iterate through all the posterior
// data combinations
for ($loop1='1'; $loop1<=$Loop1and3; $loop1++) {
for ($loop2='1'; $loop2<=$Loop2and4; $loop2++) {
for ($loop3='1'; $loop3<=$Loop1and3; $loop3++) {
for ($loop4='1'; $loop4<=$Loop2and4; $loop4++) {

$BaseRateTries[$iteration]++;

// Convert the posterior frequencies to percentages of the
// relevant hypothesis base rate. Round everything to 10
// decimals because PHP can mess up the recall of integers -
// otherwise '5' may be returned as '4.99999999'
$PercentA1 = round($loop1 / ($BR1*100),10);
$PercentB1 = round($loop2 / ($BR2*100),10);
$PercentA2 = round($loop3 / ($BR1*100),10);
$PercentB2 = round($loop4 / ($BR2*100),10);

// Actual Bayes Theorem figure for the whole matrix
$BayesNumerator = round($BR1*$PercentA1*$PercentA2,10);
$BayesDenominator = $BayesNumerator + round($BR2*$PercentB1*
    $PercentB2,10);
$BayesFigure = round($BayesNumerator/$BayesDenominator,10);
$AvBayesEstimate[$iteration]=$AvBayesEstimate[$iteration]+
    $BayesFigure;

```

```

// Representation 1 = Bayes Theorem figure if choose
// the pair D1|H1 and D1|H2
$Representation1Numerator = round($BR1*$PercentA1*0.5,10);
$Representation1Denominator = $Representation1Numerator +
    round($BR2*$PercentB1*0.5,10);
$Representation1Figure = round($Representation1Numerator/
    $Representation1Denominator,10);
$Buffer1 = $Representation1Figure;
$Representation1Figure = round(abs($Representation1Figure -
    $BayesFigure),10);
$AvRowEstimate[$iteration] = $AvRowEstimate[$iteration]+
    $Buffer1;

// Representation 2 = Bayes Theorem figure if choose
// the column pair D1|H1 and D2|H1
$Representation2Numerator = round($BR1*$PercentA1*$PercentA2
    ,10);
$Representation2Denominator = $Representation2Numerator +
    round($BR2*0.5*0.5,10);
$Representation2Figure = round($Representation2Numerator/
    $Representation2Denominator,10);
$Buffer2 = $Representation2Figure;
$Representation2Figure = round(abs($Representation2Figure -
    $BayesFigure),10);
$AvColumnEstimate[$iteration] = $AvColumnEstimate[$iteration
    ]+$Buffer2;

// Representation 3 = Bayes Theorem figure if choose
// the diagonal pair D1|H1 and D2|H2
$Representation3Numerator = round($BR1*$PercentA1*0.5,10);
$Representation3Denominator = $Representation3Numerator +
    round($BR2*0.5*$PercentB2,10);
$Representation3Figure = round($Representation3Numerator/
    $Representation3Denominator,10);
$Representation3Figure = round(abs($Representation3Figure -
    $BayesFigure),10);

// Representation 4 = Crupi et al. selection strategy.
// Decide which hypothesis would be chosen and match
// its estimate. No decision = no estimate
if (round($Loop1and3*$PercentA1*0.5,2) > round($Loop2and4
    *0.5*0.5,2)) {
$Representation4Figure = $Representation1Figure;
$AvCrupiEstimate[$iteration] = $AvCrupiEstimate[$iteration]+
    $Buffer2;
}
if (round($Loop1and3*$PercentA1*0.5,2) < round($Loop2and4
    *0.5*0.5,2)) {
$Representation4Figure = $Representation2Figure;
$AvCrupiEstimate[$iteration] = $AvCrupiEstimate[$iteration]+
    $Buffer1;
}

```

```

}
if (round($Loop1and3*$PercentA1*0.5,2) == round($Loop2and4
    *0.5*0.5,2)) {
$Representation4Figure = '';
$AvCrupiEstimate[$iteration] = $AvCrupiEstimate[$iteration]+
    $Buffer1;
}

if ($Representation1Figure<$Representation2Figure) {
$RowCorrect[$iteration]++;
$ColumnWrong[$iteration]++;
$DiagonalCorrect[$iteration]++;

if ($Representation4Figure==$Representation1Figure) {
$CrupiCorrect[$iteration]++;
} else {
$CrupiWrong[$iteration]++;
}
}

if ($Representation2Figure<$Representation1Figure) {
$RowWrong[$iteration]++;
$ColumnCorrect[$iteration]++;
$DiagonalWrong[$iteration]++;

if ($Representation4Figure==$Representation2Figure) {
$CrupiCorrect[$iteration]++;
} else {
$CrupiWrong[$iteration]++;
}
}

}

}
}
}
}
}

// Add the statistics for each base rate to the output string
for ($iteration='1'; $iteration<='9'; $iteration++) {
$Output.='Base Rate: 0.'.$iteration.':0.'. (10-$iteration).'
    Number Of Tries: '.$BaseRateTries[$iteration].PHP_EOL;
$Output.='Total Row Correct: '.$RowCorrect[$iteration].'
    Total Row Wrong: '.$RowWrong[$iteration].' Percentage
    Correct: '.round(($RowCorrect[$iteration]/($RowCorrect[
        $iteration]+$RowWrong[$iteration]))*100,3).PHP_EOL;
$Output.='Total Column Correct: '.$ColumnCorrect[$iteration].
    ' Total Column Wrong: '.$ColumnWrong[$iteration].'

```

```

    Percentage Correct: '.round(($ColumnCorrect[$iteration]/(
    $ColumnCorrect[$iteration]+$ColumnWrong[$iteration]))
    *100,3).PHP_EOL;
$Output.='Total Diagonal Correct: '.$DiagonalCorrect[
    $iteration].' Total Diagonal Wrong: '.$DiagonalWrong[
    $iteration].' Percentage Correct: '.round((
    $DiagonalCorrect[$iteration]/($DiagonalCorrect[$iteration]
    +$DiagonalWrong[$iteration]))*100,3).PHP_EOL;
$Output.='Total Crupi et al. Correct: '.$CrupiCorrect[
    $iteration].' Total Crupi et al. Wrong: '.$CrupiWrong[
    $iteration].' Percentage Correct: '.round((($CrupiCorrect[
    $iteration]/($CrupiCorrect[$iteration]+$CrupiWrong[
    $iteration]))*100,3).' Total Crupi et al. Tries: '.
    $CrupiTries[$iteration].PHP_EOL;
$Output.='Average Bayes\' Estimate: '.round(($AvBayesEstimate
    [$iteration]/$BaseRateTries[$iteration]),4).PHP_EOL;
$Output.='Average Row Estimate: '.round(($AvRowEstimate[
    $iteration]/$BaseRateTries[$iteration]),4).PHP_EOL;
$Output.='Average Column Estimate: '.round(($AvColumnEstimate
    [$iteration]/$BaseRateTries[$iteration]),4).PHP_EOL;
$Output.='Average Crupi et al. Estimate: '.round((
    $AvCrupiEstimate[$iteration]/$BaseRateTries[$iteration])
    ,4).PHP_EOL.PHP_EOL;

// Generate the statistics for the entire sample space while
// we're looping through the output by base rate
$TotalRowCorrect = $TotalRowCorrect+$RowCorrect[$iteration];
$TotalRowWrong = $TotalRowWrong+$RowWrong[$iteration];
$TotalColumnCorrect = $TotalColumnCorrect+$ColumnCorrect[
    $iteration];
$TotalColumnWrong = $TotalColumnWrong+$ColumnWrong[$iteration
    ];
$TotalDiagonalCorrect = $TotalDiagonalCorrect+
    $DiagonalCorrect[$iteration];
$TotalDiagonalWrong = $TotalDiagonalWrong+$DiagonalWrong[
    $iteration];
$TotalCrupiCorrect = $TotalCrupiCorrect+$CrupiCorrect[
    $iteration];
$TotalCrupiWrong = $TotalCrupiWrong+$CrupiWrong[$iteration];
$TotalCrupiTries = $TotalCrupiTries+$CrupiTries[$iteration];
$TotalTries = $TotalTries+$BaseRateTries[$iteration];
$TotalBayesEstimate = $TotalBayesEstimate+($AvBayesEstimate[
    $iteration]/$BaseRateTries[$iteration]);
$TotalRowEstimate = $TotalRowEstimate+($AvRowEstimate[
    $iteration]/$BaseRateTries[$iteration]);
$TotalColumnEstimate = $TotalColumnEstimate+(
    $AvColumnEstimate[$iteration]/$BaseRateTries[$iteration]);
$TotalCrupiEstimate = $TotalCrupiEstimate+($AvCrupiEstimate[
    $iteration]/$BaseRateTries[$iteration]);
}

```



```

// Add the statistics for the entire sample space to
// the output string
$Output.='Total Number Of Tries: '.$TotalTries.PHP_EOL;
$Output.='Total Row Correct: '.$TotalRowCorrect.' Total Row
Wrong: '.$TotalRowWrong.' Total Row Percentage Correct: '.
round(($TotalRowCorrect/($TotalRowCorrect+$TotalRowWrong))
*100,3).PHP_EOL;
$Output.='Total Column Correct: '.$TotalColumnCorrect.' Total
Column Wrong: '.$TotalColumnWrong.' Total Column
Percentage Correct: '.round(($TotalColumnCorrect/(
$TotalColumnCorrect+$TotalColumnWrong))*100,3).PHP_EOL;
$Output.='Total Diagonal Correct: '.$TotalDiagonalCorrect.'
Total Diagonal Wrong: '.$TotalDiagonalWrong.' Total
Diagonal Percentage Correct: '.round((
$TotalDiagonalCorrect/($TotalDiagonalCorrect+
$TotalDiagonalWrong))*100,3).PHP_EOL;
$Output.='Total Crupi et al. Correct: '.$TotalCrupiCorrect.'
Total Crupi et al. Wrong: '.$TotalCrupiWrong.' Total Crupi
et al. Percentage Correct: '.round(($TotalCrupiCorrect/(
$TotalCrupiCorrect+$TotalCrupiWrong))*100,3).' Total Crupi
et al. Tries: '.$TotalCrupiTries.PHP_EOL;
$Output.='Average Bayes\'s Estimate: '.round((
$TotalBayesEstimate/9),4).PHP_EOL;
$Output.='Average Row Estimate: '.round(($TotalRowEstimate/9)
,4).PHP_EOL;
$Output.='Average Column Estimate: '.round((
$TotalColumnEstimate/9),4).PHP_EOL;
$Output.='Average Crupi et al. Estimate: '.round((
$TotalCrupiEstimate/9),4).PHP_EOL;

// Display the output string
echo $Output;

// Finish things up gracefully
exit();

?>

```

A.2 Modelling code for Table 2.2

```
<?php

/*****
/*
/* This code iterates through all prior and posterior
/* data for a 2x2 contingency table in 0.1 increments,
/* and calculates for each of 4 selection strategies
/* whether the correct ordinal decision is made.
/*
/*
*****/

// PHP/Zend framework for ease and portability

// Initialise arrays and strings
$ColumnCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$ColumnWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$RowCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$RowWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$DiagonalCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$DiagonalWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$CrupiCorrect = array(0,0,0,0,0,0,0,0,0,0,0);
$CrupiWrong = array(0,0,0,0,0,0,0,0,0,0,0);
$CrupiTries = array(0,0,0,0,0,0,0,0,0,0,0);
$BaseRateTries = array(0,0,0,0,0,0,0,0,0,0,0);
$TotalRowCorrect = '0';
$TotalRowWrong = '0';
$TotalColumnCorrect = '0';
$TotalColumnWrong = '0';
$TotalDiagonalCorrect = '0';
$TotalDiagonalWrong = '0';
$TotalCrupiCorrect = '0';
$TotalCrupiWrong = '0';
$TotalCrupiTries = '0';
$TotalTries = '0';
$Output='';

$BR1 = '0';
$BR2 = '1';
$Loop1and3 = '0';
$Loop2and4 = '100';

// Start the loop to iterate through the base rates
for ($iteration='1'; $iteration<='9'; $iteration++) {

$BR1 = $BR1+0.1;
$BR2 = $BR2-0.1;
$Loop1and3 = $Loop1and3+10;
$Loop2and4 = $Loop2and4-10;
```

```

// Start the loops to iterate through all the posterior
// data combinations
for ($loop1='1'; $loop1<=$Loop1and3; $loop1++) {
for ($loop2='1'; $loop2<=$Loop2and4; $loop2++) {
for ($loop3='1'; $loop3<=$Loop1and3; $loop3++) {
for ($loop4='1'; $loop4<=$Loop2and4; $loop4++) {

$BaseRateTries[$iteration]++;

// Convert the posterior frequencies to percentages of the
// relevant hypothesis base rate. Round everything to 10
// decimals because PHP can mess up the recall of integers -
// otherwise '5' may be returned as '4.99999999'
$PercentA1 = round($loop1 / ($BR1*100),10);
$PercentB1 = round($loop2 / ($BR2*100),10);
$PercentA2 = round($loop3 / ($BR1*100),10);
$PercentB2 = round($loop4 / ($BR2*100),10);

// Actual Bayes Theorem figure for the whole matrix
$BayesNumerator = round($BR1*$PercentA1*$PercentA2,10);
$BayesDenominator = $BayesNumerator + round($BR2*$PercentB1*
    $PercentB2,10);
$BayesFigure = round($BayesNumerator/$BayesDenominator,10);

// Representation 1 = Bayes Theorem figure if choose
// the pair D1|H1 and D1|H2
$Representation1Numerator = round($BR1*$PercentA1*0.5,10);
$Representation1Denominator = $Representation1Numerator +
    round($BR2*$PercentB1*0.5,10);
$Representation1Figure = round($Representation1Numerator/
    $Representation1Denominator,10);

// Representation 2 = Bayes Theorem figure if choose
// the column pair D1|H1 and D2|H1
$Representation2Numerator = round($BR1*$PercentA1*$PercentA2
    ,10);
$Representation2Denominator = $Representation2Numerator +
    round($BR2*0.5*0.5,10);
$Representation2Figure = round($Representation2Numerator/
    $Representation2Denominator,10);

// Representation 3 = Bayes Theorem figure if choose
// the diagonal pair D1|H1 and D2|H2
$Representation3Numerator = round($BR1*$PercentA1*0.5,10);
$Representation3Denominator = $Representation3Numerator +
    round($BR2*0.5*$PercentB2,10);
$Representation3Figure = round($Representation3Numerator/
    $Representation3Denominator,10);

// Work out if choosing the pair D1|H1 and D1|H2
//produces the correct answer or not

```

```

if (((($BayesFigure < 0.5) && ($Representation1Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation1Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation1Figure
    == 0.5 ))) {
$RowCorrect[$iteration]++;
} else {
$RowWrong[$iteration]++;
}

// Work out if choosing the column pair D1|H1
// and D2|H1 produces the correct answer or not
if (((($BayesFigure < 0.5) && ($Representation2Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation2Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation2Figure
    == 0.5 ))) {
$ColumnCorrect[$iteration]++ ;
} else {
$ColumnWrong[$iteration]++ ;
}

// Work out if choosing the diagonal pair D1|H1
// and D2|H2 produces the correct answer or not
if (((($BayesFigure < 0.5) && ($Representation3Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation3Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation3Figure
    == 0.5 ))) {
$DiagonalCorrect[$iteration]++ ;
} else {
$DiagonalWrong[$iteration]++ ;
}

// Calculate which selection the Crupi et al.
// strategy makes and see if it's right.
// This time round everything to 2 decimals
// to make sure we've got the right numbers.
if (round($Loop1and3*$PercentA1*0.5,2) > round($Loop2and4
    *0.5*0.5,2)) {
$CrupiTries[$iteration]++;
if (((($BayesFigure < 0.5) && ($Representation2Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation2Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation2Figure
    == 0.5 ))) {
$CrupiCorrect[$iteration]++ ;
} else {
$CrupiWrong[$iteration]++ ;
}
}

if (round($Loop1and3*$PercentA1*0.5,2) < round($Loop2and4
    *0.5*0.5,2)) {
$CrupiTries[$iteration]++;

```

```

if (((($BayesFigure < 0.5) && ($Representation1Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation1Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation1Figure
    == 0.5 ))) {
$CrupiCorrect[$iteration]++ ;
} else {
$CrupiWrong[$iteration]++ ;
}
}

if (round($Loop1and3*$PercentA1*0.5,2) == round($Loop2and4
    *0.5*0.5,2)) {
// Nothing to do here ;
}

}
}
}
}
}

// Add the statistics for each base rate to the output string
for ($iteration='1'; $iteration<='9'; $iteration++) {
$Output.='Base Rate: 0.'.$iteration.':0.'.(10-$iteration).'
    Number Of Tries: '.$BaseRateTries[$iteration].PHP_EOL;
$Output.='Total Row Correct: '.$RowCorrect[$iteration].'
    Total Row Wrong: '.$RowWrong[$iteration].' Percentage
    Correct: '.round(($RowCorrect[$iteration]/($RowCorrect[
    $iteration]+$RowWrong[$iteration]))*100,3).PHP_EOL;
$Output.='Total Column Correct: '.$ColumnCorrect[$iteration].
    ' Total Column Wrong: '.$ColumnWrong[$iteration].'
    Percentage Correct: '.round(($ColumnCorrect[$iteration]/(
    $ColumnCorrect[$iteration]+$ColumnWrong[$iteration]))
    *100,3).PHP_EOL;
$Output.='Total Diagonal Correct: '.$DiagonalCorrect[
    $iteration].' Total Diagonal Wrong: '.$DiagonalWrong[
    $iteration].' Percentage Correct: '.round((
    $DiagonalCorrect[$iteration]/($DiagonalCorrect[$iteration
    ]+$DiagonalWrong[$iteration]))*100,3).PHP_EOL;
$Output.='Total Crupi et al. Correct: '.$CrupiCorrect[
    $iteration].' Total Crupi et al. Wrong: '.$CrupiWrong[
    $iteration].' Percentage Correct: '.round(($CrupiCorrect[
    $iteration]/($CrupiCorrect[$iteration]+$CrupiWrong[
    $iteration]))*100,3).' Total Crupi et al. Tries: '.
    $CrupiTries[$iteration].PHP_EOL.PHP_EOL;

// Generate the statistics for the entire sample space while
// we're looping through the output by base rate
$TotalRowCorrect = $TotalRowCorrect+$RowCorrect[$iteration];
$TotalRowWrong = $TotalRowWrong+$RowWrong[$iteration];
$TotalColumnCorrect = $TotalColumnCorrect+$ColumnCorrect[

```

```

    $iteration];
$TotalColumnWrong = $TotalColumnWrong+$ColumnWrong[$iteration
];
$TotalDiagonalCorrect = $TotalDiagonalCorrect+
    $DiagonalCorrect[$iteration];
$TotalDiagonalWrong = $TotalDiagonalWrong+$DiagonalWrong[
    $iteration];
$TotalCrupiCorrect = $TotalCrupiCorrect+$CrupiCorrect[
    $iteration];
$TotalCrupiWrong = $TotalCrupiWrong+$CrupiWrong[$iteration];
$TotalCrupiTries = $TotalCrupiTries+$CrupiTries[$iteration];
$TotalTries = $TotalTries+$BaseRateTries[$iteration];
}

// Add the statistics for the entire sample space to
// the output string
$Output.='Total Number Of Tries: '.$TotalTries.PHP_EOL;
$Output.='Total Row Correct: '.$TotalRowCorrect.' Total Row
Wrong: '.$TotalRowWrong.' Total Row Percentage Correct: '.
round(($TotalRowCorrect/($TotalRowCorrect+$TotalRowWrong))
*100,3).PHP_EOL;
$Output.='Total Column Correct: '.$TotalColumnCorrect.' Total
Column Wrong: '.$TotalColumnWrong.' Total Column
Percentage Correct: '.round(($TotalColumnCorrect/(
$TotalColumnCorrect+$TotalColumnWrong))*100,3).PHP_EOL;
$Output.='Total Diagonal Correct: '.$TotalDiagonalCorrect.'
Total Diagonal Wrong: '.$TotalDiagonalWrong.' Total
Diagonal Percentage Correct: '.round((
$TotalDiagonalCorrect/($TotalDiagonalCorrect+
$TotalDiagonalWrong))*100,3).PHP_EOL;
$Output.='Total Crupi et al. Correct: '.$TotalCrupiCorrect.'
Total Crupi et al. Wrong: '.$TotalCrupiWrong.' Total Crupi
et al. Percentage Correct: '.round(($TotalCrupiCorrect/(
$TotalCrupiCorrect+$TotalCrupiWrong))*100,3).' Total Crupi
et al. Tries: '.$TotalCrupiTries.PHP_EOL;

// Display the output string
echo $Output;

// Finish things up gracefully
exit();

?>

```

A.3 Modelling code for Table 2.3

```
<?php
```

```

/*****
/*
/* This code iterates through all prior and posterior
/* data for a 2x2 contingency table in 0.1 increments,
/* and calculates for each of 5 selection strategies
/* whether the correct ordinal decision is made.
/*
/* A minimum value of 0.5 is assumed for D1|H2.
/* This changes the estimated value for D1|H2 for the
/* Crupi et al. strategy to 0.75, and to 0.25 for the
/* Information Theory strategy.
/*
/* Note that for the Information Theory strategy the
/* assumed value of 0.25 affects hypothesis selection
/* only. For the calculation of the p-value an
/* assumed value of 0.75 is used.
/*
*****/

// PHP/Zend framework for ease and portability

// Initialise arrays and strings
$ColumnCorrect = array(0,0,0,0,0,0,0,0,0,0);
$ColumnWrong = array(0,0,0,0,0,0,0,0,0,0);
$RowCorrect = array(0,0,0,0,0,0,0,0,0,0);
$RowWrong = array(0,0,0,0,0,0,0,0,0,0);
$DiagonalCorrect = array(0,0,0,0,0,0,0,0,0,0);
$DiagonalWrong = array(0,0,0,0,0,0,0,0,0,0);
$CrupiCorrect = array(0,0,0,0,0,0,0,0,0,0);
$CrupiWrong = array(0,0,0,0,0,0,0,0,0,0);
$CrupiTries = array(0,0,0,0,0,0,0,0,0,0);
$InfoCorrect = array(0,0,0,0,0,0,0,0,0,0);
$InfoWrong = array(0,0,0,0,0,0,0,0,0,0);
$InfoTries = array(0,0,0,0,0,0,0,0,0,0);
$BaseRateTries = array(0,0,0,0,0,0,0,0,0,0);
$TotalRowCorrect = '0';
$TotalRowWrong = '0';
$TotalColumnCorrect = '0';
$TotalColumnWrong = '0';
$TotalDiagonalCorrect = '0';
$TotalDiagonalWrong = '0';
$TotalCrupiCorrect = '0';
$TotalCrupiWrong = '0';
$TotalCrupiTries = '0';
$TotalInfoCorrect = '0';
$TotalInfoWrong = '0';
$TotalInfoTries = '0';

```

```

$TotalTries = '0';
$Output='';

$BR1 = '0';
$BR2 = '1';
$Loop1and3 = '0';
$Loop2and4 = '100';

// Start the loop to iterate through the base rates
for ($iteration='1'; $iteration<='9'; $iteration++) {

$BR1 = $BR1+0.1;
$BR2 = $BR2-0.1;
$Loop1and3 = $Loop1and3+10;
$Loop2and4 = $Loop2and4-10;

// Start the loops to iterate through all the posterior
// data combinations
for ($loop1='1'; $loop1<=$Loop1and3; $loop1++) {
for ($loop2='1'; $loop2<=$Loop2and4; $loop2++) {
for ($loop3='1'; $loop3<=$Loop1and3; $loop3++) {
for ($loop4='1'; $loop4<=$Loop2and4; $loop4++) {

// Convert the posterior frequencies to percentages of the
// relevant hypothesis base rate. Round everything to 10
// decimals because PHP can mess up the recall of integers -
// otherwise '5' may be returned as '4.99999999'
$PercentA1 = round($loop1 / ($BR1*100),10);
$PercentB1 = round($loop2 / ($BR2*100),10);
$PercentA2 = round($loop3 / ($BR1*100),10);
$PercentB2 = round($loop4 / ($BR2*100),10);

if ($PercentB1>=0.5) {

$BaseRateTries[$iteration]++;

// Actual Bayes Theorem figure for the whole matrix
$BayesNumerator = round($BR1*$PercentA1*$PercentA2,10);
$BayesDenominator = $BayesNumerator + round($BR2*$PercentB1*
    $PercentB2,10);
$BayesFigure = round($BayesNumerator/$BayesDenominator,10);

// Representation 1 = Bayes Theorem figure if choose
// the pair D1|H1 and D1|H2
$Representation1Numerator = round($BR1*$PercentA1*0.5,10);
$Representation1Denominator = $Representation1Numerator +
    round($BR2*$PercentB1*0.5,10);
$Representation1Figure = round($Representation1Numerator/
    $Representation1Denominator,10);

```



```

// Representation 2 = Bayes Theorem figure if choose
// the column pair D1|H1 and D2|H1
$Representation2Numerator = round($BR1*$PercentA1*$PercentA2
,10);
$Representation2Denominator = $Representation2Numerator +
    round($BR2*0.75*0.5,10);
$Representation2Figure = round($Representation2Numerator/
    $Representation2Denominator,10);

// Representation 3 = Bayes Theorem figure if choose
// the diagonal pair D1|H1 and D2|H2
$Representation3Numerator = round($BR1*$PercentA1*0.5,10);
$Representation3Denominator = $Representation3Numerator +
    round($BR2*0.75*$PercentB2,10);
$Representation3Figure = round($Representation3Numerator/
    $Representation3Denominator,10);

// Work out if choosing the pair D1|H1 and D1|H2
// produces the correct answer or not
if (((($BayesFigure < 0.5) && ($Representation1Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation1Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation1Figure
    == 0.5 ))) {
$RowCorrect[$iteration]++;
} else {
$RowWrong[$iteration]++;
}

// Work out if choosing the column pair D1|H1
// and D2|H1 produces the correct answer or not
if (((($BayesFigure < 0.5) && ($Representation2Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation2Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation2Figure
    == 0.5 ))) {
    $ColumnCorrect[$iteration]++ ;
} else {
    $ColumnWrong[$iteration]++ ;
}

// Work out if choosing the diagonal pair D1|H1
// and H2/D2 produces the correct answer or not
if (((($BayesFigure < 0.5) && ($Representation3Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation3Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation3Figure
    == 0.5 ))) {
    $DiagonalCorrect[$iteration]++ ;
} else {
    $DiagonalWrong[$iteration]++ ;
}

// Calculate which selection the Crupi et al.

```

```

// strategy makes and see if it's right.
// This time round everything to 2 decimals
// to make sure we've got the right numbers.
if (round($Loop1and3*$PercentA1*0.5,2) > round($Loop2and4
    *0.75*0.5,2)) {
$CrupiTries[$iteration]++;
if (((($BayesFigure < 0.5) && ($Representation2Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation2Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation2Figure
    == 0.5 ))) {
$CrupiCorrect[$iteration]++ ;
} else {
$CrupiWrong[$iteration]++ ;
}
}

if (round($Loop1and3*$PercentA1*0.5,2) < round($Loop2and4
    *0.75*0.5,2)) {
$CrupiTries[$iteration]++;
if (((($BayesFigure < 0.5) && ($Representation1Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation1Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation1Figure
    == 0.5 ))) {
$CrupiCorrect[$iteration]++ ;
} else {
$CrupiWrong[$iteration]++ ;
}
}

if (round($Loop1and3*$PercentA1*0.5,2) == round($Loop2and4
    *0.75*0.5,2)) {
// Nothing to do here ;)
}

// Calculate which selection the Information
// theoretic strategy makes and see if it's right.
// This time round everything to 2 decimals
// to make sure we've got the right numbers
if (round($Loop1and3*$PercentA1*0.5,2) > round($Loop2and4
    *0.25*0.5,2)) {
$InfoTries[$iteration]++;
if (((($BayesFigure < 0.5) && ($Representation2Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation2Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation2Figure
    == 0.5 ))) {
$InfoCorrect[$iteration]++ ;
} else {
$InfoWrong[$iteration]++ ;
}
}
}

```

```

if (round($Loop1and3*$PercentA1*0.5,2) < round($Loop2and4
    *0.25*0.5,2)) {
$InfoTries[$iteration]++;
if (((($BayesFigure < 0.5) && ($Representation1Figure < 0.5 ))
    || (($BayesFigure > 0.5) && ($Representation1Figure > 0.5
    )) || (($BayesFigure == 0.5) && ($Representation1Figure
    == 0.5 ))) {
$InfoCorrect[$iteration]++ ;
} else {
$InfoWrong[$iteration]++ ;
}
}

if (round($Loop1and3*$PercentA1*0.5,2) == round($Loop2and4
    *0.25*0.5,2)) {
// Nothing to do here ;)
}

}

}
}
}
}

// Add the statistics for each base rate to the output string
for ($iteration='1'; $iteration<='9'; $iteration++) {
$Output.='Base Rate: 0.'.$iteration.':0.'. (10-$iteration).'
    Number Of Tries: '.$BaseRateTries[$iteration].PHP_EOL;
$Output.='Total Row Correct: '.$RowCorrect[$iteration].'
    Total Row Wrong: '.$RowWrong[$iteration].' Percentage
    Correct: '.round(($RowCorrect[$iteration]/($RowCorrect[
    $iteration]+$RowWrong[$iteration]))*100,3).PHP_EOL;
$Output.='Total Column Correct: '.$ColumnCorrect[$iteration].
    ' Total Column Wrong: '.$ColumnWrong[$iteration].'
    Percentage Correct: '.round(($ColumnCorrect[$iteration]/(
    $ColumnCorrect[$iteration]+$ColumnWrong[$iteration]))
    *100,3).PHP_EOL;
$Output.='Total Diagonal Correct: '.$DiagonalCorrect[
    $iteration].' Total Diagonal Wrong: '.$DiagonalWrong[
    $iteration].' Percentage Correct: '.round((
    $DiagonalCorrect[$iteration]/($DiagonalCorrect[$iteration
    ]+$DiagonalWrong[$iteration]))*100,3).PHP_EOL;
$Output.='Total Crupi et al. Correct: '.$CrupiCorrect[
    $iteration].' Total Crupi et al. Wrong: '.$CrupiWrong[
    $iteration].' Percentage Correct: '.round(($CrupiCorrect[
    $iteration]/($CrupiCorrect[$iteration]+$CrupiWrong[
    $iteration]))*100,3).' Total Crupi et al. Tries: '.
    $CrupiTries[$iteration].PHP_EOL;
$Output.='Total Infomation Theory Correct: '.$InfoCorrect[

```

```

$iteration]. ' Total Information Theory Wrong: ' . $InfoWrong
[$iteration]. ' Percentage Correct: ' . round(($InfoCorrect[
$iteration]/($InfoCorrect[$iteration]+$InfoWrong[
$iteration]))*100,3). ' Total Information Theory Tries: ' .
$InfoTries[$iteration]. PHP_EOL. PHP_EOL;

// Generate the statistics for the entire sample space while
// we're looping through the output by base rate
$TotalRowCorrect = $TotalRowCorrect+$RowCorrect[$iteration];
$TotalRowWrong = $TotalRowWrong+$RowWrong[$iteration];
$TotalColumnCorrect = $TotalColumnCorrect+$ColumnCorrect[
$iteration];
$TotalColumnWrong = $TotalColumnWrong+$ColumnWrong[$iteration
];
$TotalDiagonalCorrect = $TotalDiagonalCorrect+
$DiagonalCorrect[$iteration];
$TotalDiagonalWrong = $TotalDiagonalWrong+$DiagonalWrong[
$iteration];
$TotalCrupiCorrect = $TotalCrupiCorrect+$CrupiCorrect[
$iteration];
$TotalCrupiWrong = $TotalCrupiWrong+$CrupiWrong[$iteration];
$TotalCrupiTries = $TotalCrupiTries+$CrupiTries[$iteration];
$TotalInfoCorrect = $TotalInfoCorrect+$InfoCorrect[$iteration
];
$TotalInfoWrong = $TotalInfoWrong+$InfoWrong[$iteration];
$TotalInfoTries = $TotalInfoTries+$InfoTries[$iteration];
$TotalTries = $TotalTries+$BaseRateTries[$iteration];
}

// Add the statistics for the entire sample space to
// the output string
$Output.='Total Number Of Tries: ' . $TotalTries. PHP_EOL;
$Output.='Total Row Correct: ' . $TotalRowCorrect. ' Total Row
Wrong: ' . $TotalRowWrong. ' Total Row Percentage Correct: ' .
round(($TotalRowCorrect/($TotalRowCorrect+$TotalRowWrong))
*100,3). PHP_EOL;
$Output.='Total Column Correct: ' . $TotalColumnCorrect. ' Total
Column Wrong: ' . $TotalColumnWrong. ' Total Column
Percentage Correct: ' . round(($TotalColumnCorrect/(
$TotalColumnCorrect+$TotalColumnWrong))*100,3). PHP_EOL;
$Output.='Total Diagonal Correct: ' . $TotalDiagonalCorrect. '
Total Diagonal Wrong: ' . $TotalDiagonalWrong. ' Total
Diagonal Percentage Correct: ' . round((
$TotalDiagonalCorrect/($TotalDiagonalCorrect+
$TotalDiagonalWrong))*100,3). PHP_EOL;
$Output.='Total Crupi et al. Correct: ' . $TotalCrupiCorrect. '
Total Crupi et al. Wrong: ' . $TotalCrupiWrong. ' Total Crupi
et al. Percentage Correct: ' . round(($TotalCrupiCorrect/(
$TotalCrupiCorrect+$TotalCrupiWrong))*100,3). ' Total Crupi
et al. Tries: ' . $TotalCrupiTries. PHP_EOL;
$Output.='Total Information Theory Correct: ' .

```

```
$TotalInfoCorrect.' Total Information Theory Wrong: '.
$TotalInfoWrong.' Total Information Theory Percentage
Correct: '.round(($TotalInfoCorrect/($TotalInfoCorrect+
$TotalInfoWrong))*100,3).' Total Information Theory Tries:
'.$TotalInfoTries.PHP_EOL;

// Display the output string
echo $Output;

// Finish things up gracefully
exit();

?>
```

Appendix B

Presentational screenshots

B.1 Presentational screenshots for Experiments 1, 3, & 4

B.1.1 Question 1 (2x2 contingency table format)

Your friend has a car she bought a couple of years ago. It's either made by "Solus" or "Trisor", but you can't remember which. You do, however, remember that her car:

1: does over 25 miles per gallon

**2: has not had any major mechanical problems
in the two years she's owned it**

Below is a table giving some information about the cars made by the two companies. Using this information you must decide whether your friend's car was made by "Solus" or "Trisor". To help you make your decision you may select **one** further piece of information from the table by clicking on one of the three red squares.

	Solus	Trisor
The total number of cars sold by each company	1000	9000
The percentage of each make which does over 25 mpg		70%
The percentage of each make with no major mechanical problems in the last two years		

Which company made your friend's car?

Solus

Trisor

>> I am happy with my decision >>

Appendix Figure B1: Presentational screenshot of question 1 using a 2x2 contingency table format for an ordinal decision

B.1.2 Question 2 (2x2 contingency table format)

You are watching a political debate on television, but do not know to which group the Member of the European Parliament ("MEP") who is speaking belongs. From what he says you decide that he:

1: is in favour of further European integration

2: believes that more money should be spent on the NHS

Below is a table giving some information about two political groups in the European Parliament. Using this information you must decide whether the MEP belongs to the European People's Party ("EPP") or the Alliance of Liberals and Democrats for Europe ("ALDE"). To help you make your decision you may select **one** further piece of information from the table by clicking on one of the three red squares.

	EPP	ALDE
The total number of MEPs in each group	500	500
The percentage of each group's MEPs who are favour of further European integration		90%
The percentage of each group's MEPs who support spending more money on the NHS		

To which political group does the MEP belong?

EPP

ALDE

>> I am happy with my decision >>

Appendix Figure B2: Presentational screenshot of question 2 using a 2x2 contingency table format for an ordinal decision

B.1.3 Question 3 (2x2 contingency table format)

You are an undersea explorer who has just found an old water jug on one of your dives and would like to return it to the island on which it was made. Although there are many islands in the surrounding area, you know that pottery-making existed on only two of the islands. You would like to try to determine from which of these two islands the jug came by comparing its characteristics with what is known about similar water jugs that have already been discovered. You make a careful examination of the water jug you have found and note that:

1: It is made from smooth clay

2: It has a curved handle

Below is a table giving some information about the water jugs that have been previously discovered from the islands. Using this information you must decide whether your jug came from "Isla Negra" or "Isla Blanca". To help you make your decision you may select **one** further piece of information from the table by clicking on one of the three red squares.

	Isla Negra	Isla Blanca
The number of water jugs discovered from each island	500	500
The percentage of water jugs from each island that are made from smooth clay	40%	
The percentage of water jugs from each island that have a curved handle		

On which island was the water jug made?

Isla Negra

Isla Blanca

>> I am happy with my decision >>

Appendix Figure B3: Presentational screenshot of question 3 using a 2×2 contingency table format for an ordinal decision

B.1.4 Question 4 (2x2 contingency table format)

You are thinking about moving to a new mobile phone provider, but can't decide which. You make a list of your requirements as follows:

1: the contract should cost less than £30 per month

2: there should be high speed Internet access

and ask on your social networks which companies your friends would recommend for you. Below is a table giving some information about two mobile phone companies. Using this information you must decide whether to take out a contract with "SuperCell" or "MegaTel". To help you make your decision you may select **one** further piece of information from the table by clicking on one of the three red squares.

	SuperCell	MegaTel
The number of friends who are with each network	700	300
The percentage of your friend's contracts which cost under £30 per month		10%
The percentage of each network's coverage with high speed internet access		

With which company will you take out a mobile phone contract?

SuperCell

MegaTel

>> I am happy with my decision >>

Appendix Figure B4: Presentational screenshot of question 4 using a 2×2 contingency table format for an ordinal decision

B.1.5 Question 5 (2x2 contingency table format)

You are thinking about booking a holiday, but can't decide where to go.
You make a list of your requirements:

1: there should be good beaches

2: there should be a great nightlife

and look on tripadvisor.com to see where people recommend going. Below is a table giving some information about two destinations. Using this information you must decide whether to book a holiday to "Puerto Blanco" or "Villa Negra". To help you make your decision you may select **one** further piece of information from the table by clicking on one of the three red squares.

	Puerto Blanco	Villa Negra
The number of people who have been	800	200
The percentage of each destination's beaches which are rated as good	60%	
The percentage of people who rate each destination's nightlife as great		

Where will you book your holiday?

Puerto Blanco

Villa Negra

>> I am happy with my decision >>

Appendix Figure B5: Presentational screenshot of question 5 using a 2×2 contingency table format for an ordinal decision

B.1.6 Question 6 (2x2 contingency table format)

You are a market researcher for a comparison website and are investigating electricity suppliers. In order to be able to make a recommendation, you ask the visitors to your website which supplier they currently use and how they rate them for:

1: price

2: customer service

Below is a table giving some of the feedback. Using this information you must decide whether to recommend "EZelec" or "PowerPlus". To help you make your decision you may select **one** further piece of information from the table by clicking on one of the three red squares.

	EZelec	PowerPlus
The number of people with each supplier	900	100
The percentage of customers who rate the price as good or above		50%
The percentage of customers who rate customer service as good or above		

Which electricity supplier will you recommend?

EZelec

PowerPlus

>> I am happy with my decision >>

Appendix Figure B6: Presentational screenshot of question 6 using a 2x2 contingency table format for an ordinal decision

B.1.7 Question 1 (2x4 contingency table format)

Your friend has a car she bought a couple of years ago. It's either made by "Solus" or "Trisor", but you can't remember which. You do, however, remember that her car:

1: does over 25 miles per gallon

**2: has not had any major mechanical problems
in the two years she's owned it**

3: has four wheel drive

4: is a hatchback

Below is a table giving some information about the cars made by the two companies. Using this information you must decide whether your friend's car was made by "Solus" or "Trisor". To help you make your decision you may select **three** further pieces of information from the table by clicking on the red squares.

	Solus	Trisor
The total number of cars sold by each company	7000	3000
The percentage of each make which does over 25 mpg		50%
The percentage of each make with no major mechanical problems in the last two years		
The percentage of each make that has four wheel drive		
The percentage of each make that is a hatchback		

Which company made your friend's car?

Solus

Trisor

>> I am happy with my decision >>

Appendix Figure B7: Presentational screenshot of question 1 using a 2x4 contingency table format for an ordinal decision

B.1.8 Question 2 (2x4 contingency table format)

You are watching a political debate on television, but do not know to which group the Member of the European Parliament ("MEP") who is speaking belongs. From what he says you decide that he:

1: is in favour of further European integration

2: believes that more money should be spent on the NHS

3: is against reforming the Fisheries Policy

4: believes in tougher regulation of the media

Below is a table giving some information about two political groups in the European Parliament. Using this information you must decide whether the MEP belongs to the European People's Party ("EPP") or the Alliance of Liberals and Democrats for Europe ("ALDE"). To help you make your decision you may select *three* further pieces of information from the table by clicking on the red squares.

	EPP	ALDE
The total number of MEPs in each group	800	200
The percentage of each group's MEPs who are favour of further European integration		10%
The percentage of each group's MEPs who support spending more money on the NHS		
The percentage of each group's MEPs who are against reforming the Fisheries Policy		
The percentage of each group's MEPs who believe in tougher regulation of the media		

To which political group does the MEP belong?

EPP

ALDE

>> I am happy with my decision >>

Appendix Figure B8: Presentational screenshot of question 2 using a 2x4 contingency table format for an ordinal decision

B.1.9 Question 3 (2x4 contingency table format)

You are an undersea explorer who has just found an old water jug on one of your dives and would like to return it to the island on which it was made. Although there are many islands in the surrounding area, you know that pottery-making existed on only two of the islands. You would like to try to determine from which of these two islands the jug came by comparing its characteristics with what is known about similar water jugs that have already been discovered. You make a careful examination of the water jug you have found and note that:

1: It is made from smooth clay

2: It has a curved handle

3: It has an embossed design

4: It has a square base

Below is a table giving some information about the water jugs that have been previously discovered from the islands. Using this information you must decide whether your jug came from "Isla Negra" or "Isla Blanca". To help you make your decision you may select **three** further pieces of information from the table by clicking on the red squares.

	Isla Negra	Isla Blanca
The number of water jugs discovered from each island	500	500
The percentage of water jugs from each island that are made from smooth clay	60%	
The percentage of water jugs from each island that have a curved handle		
The percentage of water jugs from each island that have an embossed design		
The percentage of water jugs from each island that have a square base		

On which island was the water jug made?

Isla Negra

Isla Blanca

>> I am happy with my decision >>

Appendix Figure B9: Presentational screenshot of question 3 using a 2x4 contingency table format for an ordinal decision

B.1.10 Question 4 (2x4 contingency table format)

You are thinking about moving to a new mobile phone provider, but can't decide which. You make a list of your requirements as follows:

1: the contract should cost less than £30 per month

2: there should be high speed Internet access

3: the company should have good customer service

4: the phone should work in as many foreign countries as possible

and ask on your social networks which companies your friends would recommend for you. Below is a table giving some information about two mobile phone companies. Using this information you must decide whether to take out a contract with "SuperCell" or "MegaTel". To help you make your decision you may select **three** further pieces of information from the table by clicking on the red squares.

	SuperCell	MegaTel
The number of friends who are with each network	300	700
The percentage of your friend's contracts which cost under £30 per month		60%
The percentage of each network's coverage with high speed internet access		
The percentage of your friends who rate their network's service as good		
The percentage of countries with which each network has roaming agreements		

With which company will you take out a mobile phone contract?

SuperCell

MegaTel

>> I am happy with my decision >>

Appendix Figure B10: Presentational screenshot of question 4 using a 2×4 contingency table format for an ordinal decision

B.1.11 Question 5 (2x4 contingency table format)

You are thinking about booking a holiday, but can't decide where to go.
You make a list of your requirements:

1: there should be good beaches

2: there should be a great nightlife

3: there should be plenty to do and see

4: the holiday should be value for money

and look on tripadvisor.com to see where people recommend going. Below is a table giving some information about two destinations. Using this information you must decide whether to book a holiday to "Puerto Blanco" or "Villa Negra". To help you make your decision you may select *three* further pieces of information from the table by clicking on the red squares.

	Puerto Blanco	Villa Negra
The number of people who have been	900	100
The percentage of each destination's beaches which are rated as good	90%	
The percentage of people who rate each destination's nightlife as great		
The percentage of people who say that there is a lot to do and see		
The percentage of people who say that the holiday is value for money		

Where will you book your holiday?

Puerto Blanco

Villa Negra

>> I am happy with my decision >>

Appendix Figure B11: Presentational screenshot of question 5 using a 2×4 contingency table format for an ordinal decision

B.1.12 Question 6 (2x4 contingency table format)

You are a market researcher for a comparison website and are investigating electricity suppliers. In order to be able to make a recommendation, you ask the visitors to your website which supplier they currently use and how they rate them for:

1: price

2: customer service

3: contract flexibility

4: fault repairs

Below is a table giving some of the feedback. Using this information you must decide whether to recommend "EZelec" or "PowerPlus". To help you make your decision you may select **three** further pieces of information from the table by clicking on the red squares.

	EZelec	PowerPlus
The number of people with each supplier	800	200
The percentage of customers who rate the price as good or above		50%
The percentage of customers who rate customer service as good or above		
The percentage of customers who rate contract flexibility as good or above		
The percentage of customers who rate fault repairing as good or above		

Which electricity supplier will you recommend?

EZelec

PowerPlus

>> I am happy with my decision >>

Appendix Figure B12: Presentational screenshot of question 6 using a 2×4 contingency table format for an ordinal decision

B.1.13 Question 1 (3x4 contingency table format)

Your friend has a car she bought a couple of years ago. It's either made by "Solus", "Trisor" or "Tomcat", but you can't remember which. You do, however, remember that her car:

1: does over 25 miles per gallon

**2: has not had any major mechanical problems
in the two years she's owned it**

3: has four wheel drive

4: Is a hatchback

Below is a table giving some information about the cars made by the three companies. Using this information you must decide whether your friend's car was made by "Solus", "Trisor" or "Tomcat". To help you make your decision you may select **five** further pieces of information from the table by clicking on the red squares.

	Solus	Trisor	Tomcat
The total number of cars sold by each company	3000	5000	2000
The percentage of each make which does over 25 mpg	60%		
The percentage of each make with no major mechanical problems in the last two years			
The percentage of each make that has four wheel drive			
The percentage of each make that is a hatchback			

Which company made your friend's car?

Appendix Figure B13: Presentational screenshot of question 1 using a 3×4 contingency table format for an ordinal decision

B.1.14 Question 2 (3x4 contingency table format)

You are watching a political debate on television, but do not know to which group the Member of the European Parliament ("MEP") who is speaking belongs. From what he says you decide that he:

1: Is in favour of further European integration

2: believes that more money should be spent on the NHS

3: Is against reforming the Fisheries Policy

4: believes in tougher regulation of the media

Below is a table giving some information about three political groups in the European Parliament. Using this information you must decide whether the MEP belongs to the European People's Party ("EPP"), the Alliance of Liberals and Democrats for Europe ("ALDE") or the Progressive Democrats ("PD"). To help you make your decision you may select *five* further pieces of information from the table by clicking on the red squares.

	EPP	ALDE	PD
The total number of MEPs in each group	500	100	400
The percentage of each group's MEPs who are in favour of further European integration	80%		
The percentage of each group's MEPs who support spending more money on the NHS			
The percentage of each group's MEPs who are against reforming the Fisheries Policy			
The percentage of each group's MEPs who believe in tougher regulation of the media			

To which political group does the MEP belong?

EPP

ALDE

PD

>> I am happy with my decision >>

Appendix Figure B14: Presentational screenshot of question 2 using a 3×4 contingency table format for an ordinal decision

B.1.15 Question 3 (3x4 contingency table format)

You are an undersea explorer who has just found an old water jug on one of your dives and would like to return it to the island on which it was made. Although there are many islands in the surrounding area, you know that pottery-making existed on only three of the islands. You would like to try to determine from which of these three islands the jug came by comparing its characteristics with what is known about similar water jugs that have already been discovered. You make a careful examination of the water jug you have found and note that:

1: It is made from smooth clay

2: It has a curved handle

3: It has an embossed design

4: It has a square base

Below is a table giving some information about the water jugs that have been previously discovered from the islands. Using this information you must decide whether your jug came from "Isla Negra", "Isla Blanca" or "Isla Rosa". To help you make your decision you may select **five** further pieces of information from the table by clicking on the red squares.

	Isla Negra	Isla Blanca	Isla Rosa
The number of water jugs discovered from each island	500	100	400
The percentage of water jugs from each island that are made from smooth clay	20%		
The percentage of water jugs from each island that have a curved handle			
The percentage of water jugs from each island that have an embossed design			
The percentage of water jugs from each island that have a square base			

On which island was the water jug made?

Isla Negra

Isla Blanca

Isla Rosa

>> I am happy with my decision >>

Appendix Figure B15: Presentational screenshot of question 3 using a 3×4 contingency table format for an ordinal decision

B.1.16 Question 4 (3x4 contingency table format)

You are thinking about moving to a new mobile phone provider, but can't decide which. You make a list of your requirements as follows:

1: the contract should cost less than £30 per month

2: there should be high speed internet access

3: the company should have good customer service

4: the phone should work in as many foreign countries as possible

and ask on your social networks which companies your friends would recommend for you. Below is a table giving some information about three mobile phone companies. Using this information you must decide whether to take out a contract with "SuperCell", "MegaTel" or "FabPhones". To help you make your decision you may select **five** further pieces of information from the table by clicking on the red squares.

	SuperCell	MegaTel	FabPhones
The number of friends who are with each network	200	100	700
The percentage of your friend's contracts which cost under £30 per month		60%	
The percentage of each network's coverage with high speed internet access			
The percentage of your friends who rate their network's service as good			
The percentage of countries with which each network has roaming agreements			

With which company will you take out a mobile phone contract?

SuperCell

MegaTel

FabPhones

>> I am happy with my decision >>

Appendix Figure B16: Presentational screenshot of question 4 using a 3×4 contingency table format for an ordinal decision

B.1.17 Question 5 (3x4 contingency table format)

You are thinking about booking a holiday, but can't decide where to go.
You make a list of your requirements:

1: there should be good beaches

2: there should be a great nightlife

3: there should be plenty to do and see

4: the holiday should be value for money

and look on tripadvisor.com to see where people recommend going. Below is a table giving some information about three destinations. Using this information you must decide whether to book a holiday to "Puerto Blanco", "Villa Negra" or "Playa Rosa". To help you make your decision you may select **five** further pieces of information from the table by clicking on the red squares.

	Puerto Blanco	Villa Negra	Playa Rosa
The number of people who have been	100	100	800
The percentage of each destination's beaches which are rated as good	30%		
The percentage of people who rate each destination's nightlife as great			
The percentage of people who say that there is a lot to do and see			
The percentage of people who say that the holiday is value for money			

Where will you book your holiday?

Puerto Blanco

Villa Negra

Playa Rosa

>> I am happy with my decision >>

Appendix Figure B17: Presentational screenshot of question 5 using a 3×4 contingency table format for an ordinal decision

B.1.18 Question 6 (3x4 contingency table format)

You are a market researcher for a comparison website and are investigating electricity suppliers. In order to be able to make a recommendation, you ask the visitors to your website which supplier they currently use and how they rate them for:

1: price

2: customer service

3: contract flexibility

4: fault repairs

Below is a table giving some of the feedback. Using this information you must decide whether to recommend "EZelec", "PowerPlus" or "MegaWatts". To help you make your decision you may select **five** further pieces of information from the table by clicking on the red squares.

	EZelec	PowerPlus	MegaWatts
The number of people with each supplier	500	400	100
The percentage of customers who rate the price as good or above	70%		
The percentage of customers who rate customer service as good or above			
The percentage of customers who rate contract flexibility as good or above			
The percentage of customers who rate fault repairing as good or above			

Which electricity supplier will you recommend?

EZelec

PowerPlus

MegaWatts

>> I am happy with my decision >>

Appendix Figure B18: Presentational screenshot of question 6 using a 3×4 contingency table format for an ordinal decision

B.2 Presentational screenshots for Experiment 5

B.2.1 Question 1 (2x2 contingency table format)

Your friend has a car she bought a couple of years ago. It's either made by "Solus" or "Trisor", but you can't remember which. You do, however, remember that her car:

1: does over 25 miles per gallon

**2: has not had any major mechanical problems
in the two years she's owned it**

Below is a table giving some information about the cars made by the two companies. Using this information you must estimate the likelihood of the car having being made by either "Solus" or "Trisor". To help, you may select **one** further piece of information from the table by clicking on one of the three red squares.

	Solus	Trisor
The total number of cars sold by each company	4000	6000
The percentage of each make which does over 25 mpg	70%	
The percentage of each make with no major mechanical problems in the last two years		

What are the chances that each company made your friend's car?

(Note: the combined chances must equal 100%)

Solus: Trisor:

>> I am happy with my decisions >>

Appendix Figure B19: Presentational screenshot of question 1 using a 2×2 contingency table format with probability estimation

B.2.2 Question 2 (2x2 contingency table format)

You are watching a political debate on television, but do not know to which group the Member of the European Parliament ("MEP") who is speaking belongs. From what he says you decide that he:

1: is in favour of further European integration

2: believes that more money should be spent on the NHS

Below is a table giving some information about two political groups in the European Parliament. Using this information you must estimate the likelihood of the MEP belonging to either the European People's Party ("EPP") or the Alliance of Liberals and Democrats for Europe ("ALDE"). To help, you may select **one** further piece of information from the table by clicking on one of the three red squares.

	EPP	ALDE
The total number of MEPs in each group	700	300
The percentage of each group's MEPs who are favour of further European integration	20%	
The percentage of each group's MEPs who support spending more money on the NHS		

Give the chances that the MEP belongs to each of the political groups?

(Note: the combined chances must equal 100%)

EPP: ALDE:

>> I am happy with my decisions >>

Appendix Figure B20: Presentational screenshot of question 2 using a 2×2 contingency table format with probability estimation

B.2.3 Question 3 (2x2 contingency table format)

You are an undersea explorer who has just found an old water jug on one of your dives and would like to return it to the island on which it was made. Although there are many islands in the surrounding area, you know that pottery-making existed on only two of the islands. You would like to try to determine from which of these two islands the jug came by comparing its characteristics with what is known about similar water jugs that have already been discovered. You make a careful examination of the water jug you have found and note that:

1: It is made from smooth clay

2: It has a curved handle

Below is a table giving some information about the water jugs that have been previously discovered from the islands. Using this information you must estimate the likelihood of your jug having come from "Isla Negra" or "Isla Blanca". To help, you may select **one** further piece of information from the table by clicking on one of the three red squares.

	Isla Negra	Isla Blanca
The number of water jugs discovered from each island	700	300
The percentage of water jugs from each island that are made from smooth clay		90%
The percentage of water jugs from each island that have a curved handle		

What are the chances that your water jug came from each of the islands?

(Note: the combined chances must equal 100%)

Isla Negra: Isla Blanca:

>> I am happy with my decisions >>

Appendix Figure B21: Presentational screenshot of question 3 using a 2×2 contingency table format with probability estimation

B.2.4 Question 4 (2x2 contingency table format)

You are thinking about moving to a new mobile phone provider, but can't decide which. You make a list of your requirements as follows:

1: the contract should cost less than £30 per month

2: there should be high speed internet access

and ask on your social networks which companies your friends would recommend for you. Below is a table giving some information about two mobile phone companies, "SuperCell" and "MegaTel". Using this information you must estimate the likelihood of each company being able to meet your needs. To help, you may select **one** further piece of information from the table by clicking on one of the three red squares.

	SuperCell	MegaTel
The number of friends who are with each network	600	400
The percentage of your friend's contracts which cost under £30 per month	70%	
The percentage of each network's coverage with high speed internet access		

What are the chances that each phone company will be able to meet your needs?

(Note: the combined chances must equal 100%)

SuperCell: MegaTel:

>> I am happy with my decisions >>

Appendix Figure B22: Presentational screenshot of question 4 using a 2×2 contingency table format with probability estimation

B.2.5 Question 5 (2x2 contingency table format)

You are thinking about booking a holiday, but can't decide where to go.
You make a list of your requirements:

1: there should be good beaches

2: there should be a great nightlife

and look on tripadvisor.com to see where people recommend going. Below is a table giving some information about two destinations, "Puerto Blanco" and "Villa Negra". Using this information you must estimate the likelihood of each destination being suitable for your holiday. To help, you may select **one** further piece of information from the table by clicking on one of the three red squares.

	Puerto Blanco	Villa Negra
The number of people who have been	600	400
The percentage of each destination's beaches which are rated as good		90%
The percentage of people who rate each destination's nightlife as great		

What are the chances that each destination will be suitable for your holiday?

(Note: the combined chances must equal 100%)

Puerto Blanco: Villa Negra:

>> I am happy with my decisions >>

Appendix Figure B23: Presentational screenshot of question 5 using a 2×2 contingency table format with probability estimation

B.2.6 Question 6 (2x2 contingency table format)

You are a market researcher for a comparison website and are investigating electricity suppliers. In order to be able to make a recommendation, you ask the visitors to your website which supplier they currently use and how they rate them for:

1: price

2: customer service

Below is a table giving some of the feedback about two electricity suppliers, "EZelec" and "PowerPlus". Using this information you must estimate a rating for each supplier. To help, you may select **one** further piece of information from the table by clicking on one of the three red squares.

	EZelec	PowerPlus
The number of people with each supplier	100	900
The percentage of customers who rate the price as good or above	80%	
The percentage of customers who rate customer service as good or above		

How do you rate each of the electricity suppliers?

(Note: the combined ratings must equal 100%)

EZelec: PowerPlus:

>> I am happy with my decisions >>

Appendix Figure B24: Presentational screenshot of question 6 using a 2×2 contingency table format with probability estimation

B.2.7 Question 1 (2x4 contingency table format)

Your friend has a car she bought a couple of years ago. It's either made by "Solus" or "Trisor", but you can't remember which. You do, however, remember that her car:

1: does over 25 miles per gallon

**2: has not had any major mechanical problems
in the two years she's owned it**

3: has four wheel drive

4: is a hatchback

Below is a table giving some information about the cars made by the two companies. Using this information you must estimate the likelihood of the car having being made by either "Solus" or "Trisor". To help, you may select **three** further pieces of information from the table by clicking on the red squares.

	Solus	Trisor
The total number of cars sold by each company	4000	6000
The percentage of each make which does over 25 mpg	30%	
The percentage of each make with no major mechanical problems in the last two years		
The percentage of each make that has four wheel drive		
The percentage of each make that is a hatchback		

What are the chances that each company made your friend's car?

(Note: the combined chances must equal 100%)

Solus: Trisor:

>> I am happy with my decisions >>

Appendix Figure B25: Presentational screenshot of question 1 using a 2×4 contingency table format with probability estimation

B.2.8 Question 2 (2x4 contingency table format)

You are watching a political debate on television, but do not know to which group the Member of the European Parliament ("MEP") who is speaking belongs. From what he says you decide that he:

1: Is in favour of further European integration

2: believes that more money should be spent on the NHS

3: Is against reforming the Fisheries Policy

4: believes in tougher regulation of the media

Below is a table giving some information about two political groups in the European Parliament. Using this information you must estimate the likelihood of the MEP belonging to either the European People's Party ("EPP") or the Alliance of Liberals and Democrats for Europe ("ALDE"). To help, you may select **three** further pieces of information from the table by clicking on the red squares.

	EPP	ALDE
The total number of MEPs in each group	900	100
The percentage of each group's MEPs who are favour of further European integration	80%	
The percentage of each group's MEPs who support spending more money on the NHS		
The percentage of each group's MEPs who are against reforming the Fisheries Policy		
The percentage of each group's MEPs who believe in tougher regulation of the media		

Give the chances that the MEP belongs to each of the political groups?

(Note: the combined chances must equal 100%)

EPP: ALDE:

>> I am happy with my decisions >>

Appendix Figure B26: Presentational screenshot of question 2 using a 2×4 contingency table format with probability estimation

B.2.9 Question 3 (2x4 contingency table format)

You are an undersea explorer who has just found an old water jug on one of your dives and would like to return it to the island on which it was made. Although there are many islands in the surrounding area, you know that pottery-making existed on only two of the islands. You would like to try to determine from which of these two islands the jug came by comparing its characteristics with what is known about similar water jugs that have already been discovered. You make a careful examination of the water jug you have found and note that:

1: It is made from smooth clay

2: It has a curved handle

3: It has an embossed design

4: It has a square base

Below is a table giving some information about the water jugs that have been previously discovered from the islands. Using this information you must estimate the likelihood of your jug having come from "Isla Negra" or "Isla Blanca". To help, you may select *three* further pieces of information from the table by clicking on the red squares.

	Isla Negra	Isla Blanca
The number of water jugs discovered from each island	400	600
The percentage of water jugs from each island that are made from smooth clay		50%
The percentage of water jugs from each island that have a curved handle		
The percentage of water jugs from each island that have an embossed design		
The percentage of water jugs from each island that have a square base		

What are the chances that your water jug came from each of the islands?

(Note: the combined chances must equal 100%)

Isla Negra: Isla Blanca:

>> I am happy with my decisions >>

Appendix Figure B27: Presentational screenshot of question 3 using a 2×4 contingency table format with probability estimation

B.2.10 Question 4 (2x4 contingency table format)

You are thinking about moving to a new mobile phone provider, but can't decide which. You make a list of your requirements as follows:

1: the contract should cost less than £30 per month

2: there should be high speed internet access

3: the company should have good customer service

4: the phone should work in as many foreign countries as possible

and ask on your social networks which companies your friends would recommend for you. Below is a table giving some information about two mobile phone companies, "SuperCell" and "MegaTel". Using this information you must estimate the likelihood of each company being able to meet your needs. To help, you may select **three** further pieces of information from the table by clicking on the red squares.

	SuperCell	MegaTel
The number of friends who are with each network	100	900
The percentage of your friend's contracts which cost under £30 per month	80%	
The percentage of each network's coverage with high speed internet access		
The percentage of your friends who rate their network's service as good		
The percentage of countries with which each network has roaming agreements		

What are the chances that each phone company will be able to meet your needs?

(Note: the combined chances must equal 100%)

SuperCell: MegaTel:

>> I am happy with my decisions >>

Appendix Figure B28: Presentational screenshot of question 4 using a 2×4 contingency table format with probability estimation

B.2.11 Question 5 (2x4 contingency table format)

You are thinking about booking a holiday, but can't decide where to go.
You make a list of your requirements:

1: there should be good beaches

2: there should be a great nightlife

3: there should be plenty to do and see

4: the holiday should be value for money

and look on tripadvisor.com to see where people recommend going. Below is a table giving some information about two destinations, "Puerto Blanco" and "Villa Negra". Using this information you must estimate the likelihood of each destination being suitable for your holiday. To help, you may select **three** further pieces of information from the table by clicking on the red squares.

	Puerto Blanco	Villa Negra
The number of people who have been	300	700
The percentage of each destination's beaches which are rated as good		70%
The percentage of people who rate each destination's nightlife as great		
The percentage of people who say that there is a lot to do and see		
The percentage of people who say that the holiday is value for money		

What are the chances that each destination will be suitable for your holiday?

(Note: the combined chances must equal 100%)

Puerto Blanco: Villa Negra:

>> I am happy with my decisions >>

Appendix Figure B29: Presentational screenshot of question 5 using a 2×4 contingency table format with probability estimation

B.2.12 Question 6 (2x4 contingency table format)

You are a market researcher for a comparison website and are investigating electricity suppliers. In order to be able to make a recommendation, you ask the visitors to your website which supplier they currently use and how they rate them for:

1: price

2: customer service

3: contract flexibility

4: fault repairs

Below is a table giving some of the feedback about two electricity suppliers, "EZelec" and "PowerPlus". Using this information you must estimate a rating for each supplier. To help, you may select **three** further pieces of information from the table by clicking on the red squares.

	EZelec	PowerPlus
The number of people with each supplier	900	100
The percentage of customers who rate the price as good or above	90%	
The percentage of customers who rate customer service as good or above		
The percentage of customers who rate contract flexibility as good or above		
The percentage of customers who rate fault repairing as good or above		

How do you rate each of the electricity suppliers?

(Note: the combined ratings must equal 100%)

EZelec: PowerPlus:

>> I am happy with my decisions >>

Appendix Figure B30: Presentational screenshot of question 6 using a 2×4 contingency table format with probability estimation

B.2.13 Question 1 (3x4 contingency table format)

Your friend has a car she bought a couple of years ago. It's either made by "Solus", "Trisor" or "Tomcat", but you can't remember which. You do, however, remember that her car:

1: does over 25 miles per gallon

**2: has not had any major mechanical problems
in the two years she's owned it**

3: has four wheel drive

4: Is a hatchback

Below is a table giving some information about the cars made by the three companies. Using this information you must estimate the likelihood of the car having being made by either "Solus", "Trisor" or "Tomcat". To help, you may select *five* further pieces of information from the table by clicking on the red squares.

	Solus	Trisor	Tomcat
The total number of cars sold by each company	2000	4000	4000
The percentage of each make which does over 25 mpg			10%
The percentage of each make with no major mechanical problems in the last two years			
The percentage of each make that has four wheel drive			
The percentage of each make that is a hatchback			

What are the chances that each company made your friend's car?

(Note: the combined chances must equal 100%)

Solus: Trisor: Tomcat:

>> I am happy with my decisions >>

Appendix Figure B31: Presentational screenshot of question 1 using a 3×4 contingency table format with probability estimation

B.2.14 Question 2 (3x4 contingency table format)

You are watching a political debate on television, but do not know to which group the Member of the European Parliament ("MEP") who is speaking belongs. From what he says you decide that he:

1: is in favour of further European integration

2: believes that more money should be spent on the NHS

3: is against reforming the Fisheries Policy

4: believes in tougher regulation of the media

Below is a table giving some information about three political groups in the European Parliament. Using this information you must estimate the likelihood of the MEP belonging to either the European People's Party ("EPP"), the Alliance of Liberals and Democrats for Europe ("ALDE") or the Progressive Democrats ("PD"). To help, you may select *five* further pieces of information from the table by clicking on the red squares.

	EPP	ALDE	PD
The total number of MEPs in each group	100	100	800
The percentage of each group's MEPs who are in favour of further European integration		10%	
The percentage of each group's MEPs who support spending more money on the NHS			
The percentage of each group's MEPs who are against reforming the Fisheries Policy			
The percentage of each group's MEPs who believe in tougher regulation of the media			

Give the chances that the MEP belongs to each of the political groups?

(Note: the combined chances must equal 100%)

EPP: ALDE: PD:

>> I am happy with my decisions >>

Appendix Figure B32: Presentational screenshot of question 2 using a 3×4 contingency table format with probability estimation

B.2.15 Question 3 (3x4 contingency table format)

You are an undersea explorer who has just found an old water jug on one of your dives and would like to return it to the island on which it was made. Although there are many islands in the surrounding area, you know that pottery-making existed on only three of the islands. You would like to try to determine from which of these three islands the jug came by comparing its characteristics with what is known about similar water jugs that have already been discovered. You make a careful examination of the water jug you have found and note that:

1: It is made from smooth clay

2: It has a curved handle

3: It has an embossed design

4: It has a square base

Below is a table giving some information about the water jugs that have been previously discovered from the islands. Using this information you must estimate the likelihood of your jug having come from "Isla Negra", "Isla Blanca" or "Isla Rosa". To help, you may select *five* further pieces of information from the table by clicking on the red squares.

	Isla Negra	Isla Blanca	Isla Rosa
The number of water jugs discovered from each island	200	600	200
The percentage of water jugs from each island that are made from smooth clay			90%
The percentage of water jugs from each island that have a curved handle			
The percentage of water jugs from each island that have an embossed design			
The percentage of water jugs from each island that have a square base			

What are the chances that your water jug came from each of the islands?

(Note: the combined chances must equal 100%)

Isla Negra: Isla Blanca: Isla Rosa:

>> I am happy with my decisions >>

Appendix Figure B33: Presentational screenshot of question 3 using a 3×4 contingency table format with probability estimation

B.2.16 Question 4 (3x4 contingency table format)

You are thinking about moving to a new mobile phone provider, but can't decide which. You make a list of your requirements as follows:

1: the contract should cost less than £30 per month

2: there should be high speed Internet access

3: the company should have good customer service

4: the phone should work in as many foreign countries as possible

and ask on your social networks which companies your friends would recommend for you. Below is a table giving some information about three mobile phone companies, "SuperCell", "MegaTel" and "FabPhones". Using this information you must estimate the likelihood of each company being able to meet your needs. To help, you may select **five** further pieces of information from the table by clicking on the red squares.

	SuperCell	MegaTel	FabPhones
The number of friends who are with each network	200	200	600
The percentage of your friend's contracts which cost under £30 per month			90%
The percentage of each network's coverage with high speed internet access			
The percentage of your friends who rate their network's service as good			
The percentage of countries with which each network has roaming agreements			

What are the chances that each phone company will be able to meet your needs?

(Note: the combined chances must equal 100%)

SuperCell: MegaTel: FabPhones:

>> I am happy with my decisions >>

Appendix Figure B34: Presentational screenshot of question 4 using a 3 × 4 contingency table format with probability estimation

B.2.17 Question 5 (3x4 contingency table format)

You are thinking about booking a holiday, but can't decide where to go.
You make a list of your requirements:

1: there should be good beaches

2: there should be a great nightlife

3: there should be plenty to do and see

4: the holiday should be value for money

and look on tripadvisor.com to see where people recommend going. Below is a table giving some information about three destinations, "Puerto Blanco", "Villa Negra" and "Playa Rosa". Using this information you must estimate the likelihood of each destination being suitable for your holiday. To help, you may select **five** further pieces of information from the table by clicking on the red squares.

	Puerto Blanco	Villa Negra	Playa Rosa
The number of people who have been	800	100	100
The percentage of each destination's beaches which are rated as good		70%	
The percentage of people who rate each destination's nightlife as great			
The percentage of people who say that there is a lot to do and see			
The percentage of people who say that the holiday is value for money			

What are the chances that each destination will be suitable for your holiday?

(Note: the combined chances must equal 100%)

Puerto Blanco: Villa Negra: Playa Rosa:

>> I am happy with my decisions >>

Appendix Figure B35: Presentational screenshot of question 5 using a 3×4 contingency table format with probability estimation

B.2.18 Question 6 (3x4 contingency table format)

You are a market researcher for a comparison website and are investigating electricity suppliers. In order to be able to make a recommendation, you ask the visitors to your website which supplier they currently use and how they rate them for:

1: price

2: customer service

3: contract flexibility

4: fault repairs

Below is a table giving some of the feedback about three electricity suppliers, "EZelec", "PowerPlus" and "MegaWatts". Using this information you must estimate a rating for each supplier. To help, you may select **five** further pieces of information from the table by clicking on the red squares.

	EZelec	PowerPlus	MegaWatts
The number of people with each supplier	700	200	100
The percentage of customers who rate the price as good or above			40%
The percentage of customers who rate customer service as good or above			
The percentage of customers who rate contract flexibility as good or above			
The percentage of customers who rate fault repairing as good or above			

How do you rate each of the electricity suppliers?

(Note: the combined ratings must equal 100%)

EZelec: PowerPlus: MegaWatts:

>> I am happy with my decisions >>

Appendix Figure B36: Presentational screenshot of question 6 using a 3×4 contingency table format with probability estimation

Appendix C

Online experiment security and validation protocol

- All responses were logged to a MySQL database.
- An exercise could not be returned to once completed. Clicking the “Back” button on the browser terminated the experiment.
- All incomplete participant data sets were discarded.
- The chances of multiple responses by the same participant were minimized by the setting of an encrypted cookie on their computer (timed to expire on conclusion of the research project), and by IP address logging. Any participant who attempted to take part more than once was allowed to complete the exercises, but all their data (including their original participation) were discarded.
- Direct access to the HTML pages of the experiment was prohibited. Progress through the experiment was achieved by Javascript rewriting of the Inner-HTML element. Participant progress through the experiment was also stored, and validated at each stage, in their browser cookie. This prevented people from attempting to start the experiment from anywhere other than the initial page.
- All submissions were validated and cleansed to prevent a MySQL injection attack.
- Directory traversal attacks were prevented.

- Any attempt by a participant to either answer a question before having selected an appropriate number of contingency table data, or to select more than the required number of data, resulted in an error “pop-up” message being displayed.
- There was no restriction on the form factor used to access the experiments.

Appendix D

Participant selections

D.1 Experiment 1: Participant selections

D.1.1 First exercise

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
001	1	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.5	-	0.5
		D_2	-	-	-	0.8
002	6	Priors	0.9	0.1	0.9	0.1
		D_1	0.9	-	0.9	-
		D_2	-	-	0.4	-
003	2	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.4	-	0.4
		D_2	-	-	0.7	-
004	5	Priors	0.3	0.7	0.3	0.7
		D_1	0.3	-	0.3	0.6
		D_2	-	-	-	-
005	4	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.1	-	0.1
		D_2	-	-	-	0.6

Appendix Table D1: Participant selections for the two hypotheses, two diagnostic criteria contingency tables: First exercise

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
006	6	Priors	0.2	0.8	0.2	0.8
		D_1	0.1	-	0.1	-
		D_2	-	-	0.4	-
007	4	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.5	-	0.5
		D_2	-	-	-	0.8
008	3	Priors	0.2	0.8	0.2	0.8
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.7
009	2	Priors	0.1	0.9	0.1	0.9
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.4
010	6	Priors	0.1	0.9	0.1	0.9
		D_1	0.3	-	0.3	-
		D_2	-	-	0.7	-
011	3	Priors	0.3	0.7	0.3	0.7
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.5
012	3	Priors	0.5	0.5	0.5	0.5
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.7
013	4	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.5	-	0.5
		D_2	-	-	0.3	-
014	4	Priors	0.5	0.5	0.5	0.5
		D_1	0.9	-	0.9	-
		D_2	-	-	-	0.9
015	3	Priors	0.7	0.3	0.7	0.3
		D_1	0.7	-	0.7	-
		D_2	-	-	0.1	-

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
016	4	Priors	0.9	0.1	0.9	0.1
		D_1	0.6	-	0.6	0.4
		D_2	-	-	-	-
017	5	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.1	0.8	0.1
		D_2	-	-	-	-
018	5	Priors	0.1	0.9	0.1	0.9
		D_1	0.1	-	0.1	0.5
		D_2	-	-	-	-
019	2	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.8	-	0.8
		D_2	-	-	0.6	-
020	4	Priors	0.3	0.7	0.3	0.7
		D_1	0.9	-	0.9	0.3
		D_2	-	-	-	-
021	2	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.7	-	0.7
		D_2	-	-	-	0.8
022	2	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.1	-	0.1
		D_2	-	-	0.1	-
023	6	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.8	0.3	0.8
		D_2	-	-	-	-
024	4	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.6	-	0.6
		D_2	-	-	0.2	-
025	2	Priors	0.5	0.5	0.5	0.5
		D_1	0.2	-	0.2	0.5
		D_2	-	-	-	-

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
026	1	Priors	0.4	0.6	0.4	0.6
		D_1	0.4	-	0.4	0.7
		D_2	-	-	-	-
027	1	Priors	0.2	0.8	0.2	0.8
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.6
028	2	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.7	-	0.7
		D_2	-	-	-	0.8
029	5	Priors	0.2	0.8	0.2	0.8
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.1
030	4	Priors	0.7	0.3	0.7	0.3
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.4
031	5	Priors	0.1	0.9	0.1	0.9
		D_1	0.1	-	0.1	0.2
		D_2	-	-	-	-
032	3	Priors	0.8	0.2	0.8	0.2
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.8
033	2	Priors	0.2	0.8	0.2	0.8
		D_1	0.1	-	0.1	0.3
		D_2	-	-	-	-
034	2	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.9	0.8	0.9
		D_2	-	-	-	-
035	3	Priors	0.5	0.5	0.5	0.5
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.5

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
036	3	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.9	0.5	0.9
		D_2	-	-	-	-
037	2	Priors	0.4	0.6	0.4	0.6
		D_1	0.7	-	0.7	-
		D_2	-	-	0.5	-
038	3	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.3	-	0.3
		D_2	-	-	0.2	-
039	4	Priors	0.8	0.2	0.8	0.2
		D_1	0.2	-	0.2	-
		D_2	-	-	0.8	-
040	5	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.9	0.8	0.9
		D_2	-	-	-	-
041	4	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.6	0.6	0.6
		D_2	-	-	-	-
042	4	Priors	0.4	0.6	0.4	0.6
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.3
043	3	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.1	-	0.1
		D_2	-	-	0.5	-
044	4	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.5	-	0.5
		D_2	-	-	0.5	-
045	5	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.3	-	0.3
		D_2	-	-	-	0.1

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
046	1	Priors	0.4	0.6	0.4	0.6
		D_1	0.7	-	0.7	0.1
		D_2	-	-	-	-
047	5	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.7	0.1	0.7
		D_2	-	-	-	-
048	5	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.9	0.2	0.9
		D_2	-	-	-	-
049	5	Priors	0.8	0.2	0.8	0.2
		D_1	0.7	-	0.7	-
		D_2	-	-	-	0.3
050	4	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.3	0.2	0.3
		D_2	-	-	-	-
051	1	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.9	0.2	0.9
		D_2	-	-	-	-
052	6	Priors	0.8	0.2	0.8	0.2
		D_1	0.2	-	0.2	0.2
		D_2	-	-	-	-
053	2	Priors	0.8	0.2	0.8	0.2
		D_1	0.6	-	0.6	-
		D_2	-	-	0.2	-
054	6	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.8	0.5	0.8
		D_2	-	-	-	-
055	3	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.2	0.7	0.2
		D_2	-	-	-	-

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
056	5	Priors	0.1	0.9	0.1	0.9
		D_1	0.5	-	0.5	-
		D_2	-	-	-	0.6
057	2	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.5	-	0.5
		D_2	-	-	-	0.1
058	6	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.9	-	0.9
		D_2	-	-	0.2	-
059	1	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.2	-	0.2
		D_2	-	-	-	0.5
060	1	Priors	0.3	0.7	0.3	0.7
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.5
061	2	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.4	0.7	0.4
		D_2	-	-	-	-
062	4	Priors	0.8	0.2	0.8	0.2
		D_1	0.9	-	0.9	-
		D_2	-	-	-	0.7
063	1	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.7	-	0.7
		D_2	-	-	-	0.6
064	6	Priors	0.5	0.5	0.5	0.5
		D_1	0.5	-	0.5	0.8
		D_2	-	-	-	-
065	2	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.3	-	0.3
		D_2	-	-	0.4	-

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
066	1	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.6	0.6	0.6
		D_2	-	-	-	-
067	5	Priors	0.2	0.8	0.2	0.8
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.2
068	6	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.6	0.4	0.6
		D_2	-	-	-	-
069	1	Priors	0.9	0.1	0.9	0.1
		D_1	0.2	-	0.2	0.6
		D_2	-	-	-	-
070	5	Priors	0.4	0.6	0.4	0.6
		D_1	0.2	-	0.2	-
		D_2	-	-	0.4	-
071	3	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.4	0.7	0.4
		D_2	-	-	-	-
072	1	Priors	0.8	0.2	0.8	0.2
		D_1	0.8	-	0.8	0.9
		D_2	-	-	-	-
073	1	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.9	-	0.9
		D_2	-	-	0.7	-
074	1	Priors	0.3	0.7	0.3	0.7
		D_1	0.3	-	0.3	-
		D_2	-	-	0.4	-
075	4	Priors	0.7	0.3	0.7	0.3
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.6

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
076	1	Priors	0.7	0.3	0.7	0.3
		D_1	0.4	-	0.4	0.7
		D_2	-	-	-	-
077	5	Priors	0.5	0.5	0.5	0.5
		D_1	0.2	-	0.2	-
		D_2	-	-	0.6	-
078	3	Priors	0.8	0.2	0.8	0.2
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.6
079	3	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.6	0.5	0.6
		D_2	-	-	-	-
080	2	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.1	-	0.1
		D_2	-	-	0.6	-
081	6	Priors	0.4	0.6	0.4	0.6
		D_1	0.8	-	0.8	0.4
		D_2	-	-	-	-
082	6	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.1	-	0.1
		D_2	-	-	-	0.9
083	1	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.9	-	0.9
		D_2	-	-	0.6	-
084	5	Priors	0.3	0.7	0.3	0.7
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.3
085	1	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.2	0.7	0.2
		D_2	-	-	-	-

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
086	5	Priors	0.2	0.8	0.2	0.8
		D_1	0.7	-	0.7	-
		D_2	-	-	-	0.4
087	3	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.8	-	0.8
		D_2	-	-	-	0.1
088	4	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.5	0.4	0.5
		D_2	-	-	-	-
089	3	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.4	-	0.4
		D_2	-	-	0.2	-
090	2	Priors	0.8	0.2	0.8	0.2
		D_1	0.5	-	0.5	0.6
		D_2	-	-	-	-
091	4	Priors	0.1	0.9	0.1	0.9
		D_1	0.8	-	0.8	-
		D_2	-	-	-	0.5
092	2	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.2	-	0.2
		D_2	-	-	0.6	-
093	1	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.2	0.4	0.2
		D_2	-	-	-	-
094	4	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.1	-	0.1
		D_2	-	-	-	0.3
095	4	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.2	0.1	0.2
		D_2	-	-	-	-

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
096	5	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.2	-	0.2
		D_2	-	-	0.5	-
097	6	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.9	0.7	0.9
		D_2	-	-	-	-
098	3	Priors	0.8	0.2	0.8	0.2
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.3
099	3	Priors	0.3	0.7	0.3	0.7
		D_1	0.3	-	0.3	-
		D_2	-	-	0.3	-
100	3	Priors	0.2	0.8	0.2	0.8
		D_1	0.5	-	0.5	-
		D_2	-	-	-	0.3
101	2	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.4	0.6	0.4
		D_2	-	-	-	-
102	6	Priors	0.2	0.8	0.2	0.8
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.5
103	4	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.7	0.4	0.7
		D_2	-	-	-	-
104	6	Priors	0.7	0.3	0.7	0.3
		D_1	0.9	-	0.9	0.1
		D_2	-	-	-	-
105	5	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.3	-	0.3
		D_2	-	-	0.2	-

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
106	4	Priors	0.4	0.6	0.4	0.6
		D_1	0.4	-	0.4	-
		D_2	-	-	-	0.6
107	1	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.9	-	0.9
		D_2	-	-	-	0.8
108	4	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.6	-	0.6
		D_2	-	-	0.6	-
109	2	Priors	0.2	0.8	0.2	0.8
		D_1	0.8	-	0.8	-
		D_2	-	-	-	0.7
110	3	Priors	0.9	0.1	0.9	0.1
		D_1	0.8	-	0.8	-
		D_2	-	-	0.6	-
111	2	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.6	-	0.6
		D_2	-	-	0.8	-
112	6	Priors	0.1	0.9	0.1	0.9
		D_1	0.9	-	0.9	-
		D_2	-	-	0.7	-
113	1	Priors	0.3	0.7	0.3	0.7
		D_1	0.2	-	0.2	0.3
		D_2	-	-	-	-
114	6	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.6	-	0.6
		D_2	-	-	0.4	-
115	6	Priors	0.5	0.5	0.5	0.5
		D_1	0.7	-	0.7	-
		D_2	-	-	-	0.9

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
116	5	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.6	-	0.6
		D_2	-	-	0.7	-
117	2	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.4	-	0.4
		D_2	-	-	0.8	-
118	5	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.1	0.6	0.1
		D_2	-	-	-	-
119	4	Priors	0.3	0.7	0.3	0.7
		D_1	0.5	-	0.5	0.5
		D_2	-	-	-	-
120	2	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.3	0.4	0.3
		D_2	-	-	-	-
121	3	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.3	0.9	0.3
		D_2	-	-	-	-
122	3	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.9	-	0.9
		D_2	-	-	-	0.9
123	3	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.2	-	0.2
		D_2	-	-	0.9	-
124	4	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.1	-	0.1
		D_2	-	-	-	0.7
125	1	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.2	-	0.2
		D_2	-	-	-	0.4

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
126	2	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.1	-	0.1
		D_2	-	-	0.5	-
127	3	Priors	0.1	0.9	0.1	0.9
		D_1	0.9	-	0.9	0.7
		D_2	-	-	-	-
128	6	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.5	-	0.5
		D_2	-	-	0.6	-
129	4	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.7	0.7	0.7
		D_2	-	-	-	-
130	2	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.4	-	0.4
		D_2	-	-	0.5	-
131	4	Priors	0.2	0.8	0.2	0.8
		D_1	0.4	-	0.4	-
		D_2	-	-	-	0.1
132	2	Priors	0.9	0.1	0.9	0.1
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.5
133	3	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.4	0.4	0.4
		D_2	-	-	-	-
134	6	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.2	0.5	0.2
		D_2	-	-	-	-
135	5	Priors	0.1	0.9	0.1	0.9
		D_1	0.8	-	0.8	-
		D_2	-	-	-	0.5

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
136	4	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.3	0.8	0.3
		D_2	-	-	-	-
137	3	Priors	0.1	0.9	0.1	0.9
		D_1	0.8	-	0.8	-
		D_2	-	-	-	0.7
138	5	Priors	0.5	0.5	0.5	0.5
		D_1	0.4	-	0.4	-
		D_2	-	-	-	0.3
139	4	Priors	0.8	0.2	0.8	0.2
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.4
140	5	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.6	-	0.6
		D_2	-	-	-	0.7
141	5	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.7	0.2	0.7
		D_2	-	-	-	-
142	6	Priors	0.1	0.9	0.1	0.9
		D_1	0.5	-	0.5	-
		D_2	-	-	-	0.4
143	2	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.7	0.9	0.7
		D_2	-	-	-	-
144	6	Priors	0.4	0.6	0.4	0.6
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.6
145	3	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.1	-	0.1
		D_2	-	-	-	0.1

Appendix Table D1: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
146	2	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.4	-	0.4
		D_2	-	-	-	0.6
147	1	Priors	0.5	0.5	0.5	0.5
		D_1	0.4	-	0.4	-
		D_2	-	-	-	0.4
148	1	Priors	0.7	0.3	0.7	0.3
		D_1	0.2	-	0.2	0.6
		D_2	-	-	-	-
149	3	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.4	-	0.4
		D_2	-	-	0.6	-
150	6	Priors	0.5	0.5	0.5	0.5
		D_1	0.9	-	0.9	-
		D_2	-	-	-	0.1

D.1.2 Second exercise

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
001	1	Priors	0.1	0.9	0.1	0.9
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.5
002	5	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.1	-	0.1
		D_2	-	-	0.4	-
003	5	Priors	0.9	0.1	0.9	0.1
		D_1	0.7	-	0.7	-
		D_2	-	-	-	0.3
004	4	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.5	-	0.5
		D_2	-	-	-	0.1
005	2	Priors	0.9	0.1	0.9	0.1
		D_1	0.8	-	0.8	0.5
		D_2	-	-	-	-
006	2	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.3	-	0.3
		D_2	-	-	-	0.8
007	6	Priors	0.7	0.3	0.7	0.3
		D_1	0.5	-	0.5	-
		D_2	-	-	-	0.5
008	6	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.8	-	0.8
		D_2	-	-	0.8	-
009	4	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.5	0.6	0.5
		D_2	-	-	-	-

Appendix Table D2: Participant selections for the two hypotheses, two diagnostic criteria contingency tables: Second exercise

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
010	4	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.2	-	0.2
		D_2	-	-	0.6	-
011	5	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.9	0.1	0.9
		D_2	-	-	-	-
012	5	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.6	-	0.6
		D_2	-	-	0.9	-
013	1	Priors	0.2	0.8	0.2	0.8
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.7
014	6	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.3	-	0.3
		D_2	-	-	-	0.8
015	4	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.1	-	0.1
		D_2	-	-	0.3	-
016	5	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.8	0.7	0.8
		D_2	-	-	-	-
017	4	Priors	0.5	0.5	0.5	0.5
		D_1	0.9	-	0.9	0.9
		D_2	-	-	-	-
018	2	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.5	0.8	0.5
		D_2	-	-	-	-
019	5	Priors	0.2	0.8	0.2	0.8
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.7

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
020	6	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.8	0.8	0.8
		D_2	-	-	-	-
021	6	Priors	0.1	0.9	0.1	0.9
		D_1	0.5	-	0.5	-
		D_2	-	-	-	0.6
022	3	Priors	0.9	0.1	0.9	0.1
		D_1	0.1	-	0.1	-
		D_2	-	-	0.7	-
023	4	Priors	0.3	0.7	0.3	0.7
		D_1	0.1	-	0.1	0.4
		D_2	-	-	-	-
024	6	Priors	0.5	0.5	0.5	0.5
		D_1	0.5	-	0.5	-
		D_2	-	-	0.5	-
025	5	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.9	-	0.9
		D_2	-	-	0.9	-
026	6	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.4	-	0.4
		D_2	-	-	0.6	-
027	3	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.4	-	0.4
		D_2	-	-	-	0.9
028	4	Priors	0.2	0.8	0.2	0.8
		D_1	0.3	-	0.3	0.2
		D_2	-	-	-	-
029	1	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.1	-	0.1
		D_2	-	-	-	0.8

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
030	2	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.7	-	0.7
		D_2	-	-	0.7	-
031	1	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.3	0.2	0.3
		D_2	-	-	-	-
032	6	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.9	-	0.9
		D_2	-	-	0.1	-
033	5	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.9	0.3	0.9
		D_2	-	-	-	-
034	5	Priors	0.5	0.5	0.5	0.5
		D_1	0.2	-	0.2	0.1
		D_2	-	-	-	-
035	5	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.1	0.4	0.1
		D_2	-	-	-	-
036	4	Priors	0.8	0.2	0.8	0.2
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.3
037	1	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.1	-	0.1
		D_2	-	-	0.5	-
038	6	Priors	0.5	0.5	0.5	0.5
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.7
039	2	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.6	-	0.6
		D_2	-	-	-	0.1

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
040	1	Priors	0.8	0.2	0.8	0.2
		D_1	0.7	-	0.7	0.2
		D_2	-	-	-	-
041	2	Priors	0.9	0.1	0.9	0.1
		D_1	0.4	-	0.4	0.8
		D_2	-	-	-	-
042	6	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.7	-	0.7
		D_2	-	-	0.2	-
043	4	Priors	0.8	0.2	0.8	0.2
		D_1	0.9	-	0.9	-
		D_2	-	-	0.6	-
044	2	Priors	0.3	0.7	0.3	0.7
		D_1	0.5	-	0.5	-
		D_2	-	-	0.2	-
045	4	Priors	0.6	0.4	0.6	0.4
		D_1	0.8	-	0.8	-
		D_2	-	-	0.7	-
046	4	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.4	0.6	0.4
		D_2	-	-	-	-
047	1	Priors	0.5	0.5	0.5	0.5
		D_1	0.5	-	0.5	0.1
		D_2	-	-	-	-
048	1	Priors	0.8	0.2	0.8	0.2
		D_1	0.5	-	0.5	0.7
		D_2	-	-	-	-
049	1	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.7	0.2	0.7
		D_2	-	-	-	-

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
050	3	Priors	0.9	0.1	0.9	0.1
		D_1	0.1	-	0.1	0.9
		D_2	-	-	-	-
051	6	Priors	0.4	0.6	0.4	0.6
		D_1	0.5	-	0.5	0.7
		D_2	-	-	-	-
052	2	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.8	0.6	0.8
		D_2	-	-	-	-
053	1	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.2	0.1	0.2
		D_2	-	-	-	-
054	4	Priors	0.3	0.7	0.3	0.7
		D_1	0.5	-	0.5	0.4
		D_2	-	-	-	-
055	1	Priors	0.2	0.8	0.2	0.8
		D_1	0.9	-	0.9	-
		D_2	-	-	0.1	-
056	1	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.9	-	0.9
		D_2	-	-	-	0.7
057	3	Priors	0.7	0.3	0.7	0.3
		D_1	0.4	-	0.4	0.9
		D_2	-	-	-	-
058	5	Priors	0.8	0.2	0.8	0.2
		D_1	0.2	-	0.2	0.5
		D_2	-	-	-	-
059	2	Priors	0.7	0.3	0.7	0.3
		D_1	0.7	-	0.7	0.6
		D_2	-	-	-	-

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
060	5	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.5	-	0.5
		D_2	-	-	-	0.7
061	3	Priors	0.6	0.4	0.6	0.4
		D_1	0.3	-	0.3	0.2
		D_2	-	-	-	-
062	1	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.2	-	0.2
		D_2	-	-	-	0.7
063	5	Priors	0.3	0.7	0.3	0.7
		D_1	0.5	-	0.5	0.7
		D_2	-	-	-	-
064	2	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.1	0.2	0.1
		D_2	-	-	-	-
065	6	Priors	0.1	0.9	0.1	0.9
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.3
066	4	Priors	0.9	0.1	0.9	0.1
		D_1	0.6	-	0.6	-
		D_2	-	-	0.3	-
067	1	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.8	-	0.8
		D_2	-	-	-	0.8
068	2	Priors	0.9	0.1	0.9	0.1
		D_1	0.2	-	0.2	-
		D_2	-	-	0.9	-
069	3	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.7	0.2	0.7
		D_2	-	-	-	-

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
070	4	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.8	-	0.8
		D_2	-	-	-	0.1
071	1	Priors	0.6	0.4	0.6	0.4
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.9
072	6	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.9	-	0.9
		D_2	-	-	0.5	-
073	5	Priors	0.8	0.2	0.8	0.2
		D_1	0.3	-	0.3	-
		D_2	-	-	0.5	-
074	3	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.6	0.3	0.6
		D_2	-	-	-	-
075	3	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.8	-	0.8
		D_2	-	-	-	0.9
076	4	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.3	-	0.3
		D_2	-	-	-	0.5
077	3	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.8	0.8	0.8
		D_2	-	-	-	-
078	2	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.9	-	0.9
		D_2	-	-	0.4	-
079	1	Priors	0.8	0.2	0.8	0.2
		D_1	0.8	-	0.8	-
		D_2	-	-	0.4	-

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
080	3	Priors	0.4	0.6	0.4	0.6
		D_1	0.7	-	0.7	-
		D_2	-	-	0.2	-
081	3	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.5	-	0.5
		D_2	-	-	-	0.2
082	2	Priors	0.6	0.4	0.6	0.4
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.9
083	6	Priors	0.4	0.6	0.4	0.6
		D_1	0.1	-	0.1	0.1
		D_2	-	-	-	-
084	3	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.7	-	0.7
		D_2	-	-	0.1	-
085	2	Priors	0.4	0.6	0.4	0.6
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.3
086	2	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.5	-	0.5
		D_2	-	-	0.8	-
087	1	Priors	0.7	0.3	0.7	0.3
		D_1	0.8	-	0.8	-
		D_2	-	-	0.2	-
088	3	Priors	0.7	0.3	0.7	0.3
		D_1	0.6	-	0.6	0.5
		D_2	-	-	-	-
089	6	Priors	0.2	0.8	0.2	0.8
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.7

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
090	6	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.9	0.5	0.9
		D_2	-	-	-	-
091	5	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.7	-	0.7
		D_2	-	-	0.7	-
092	4	Priors	0.5	0.5	0.5	0.5
		D_1	0.6	-	0.6	-
		D_2	-	-	0.2	-
093	2	Priors	0.3	0.7	0.3	0.7
		D_1	0.5	-	0.5	0.5
		D_2	-	-	-	-
094	1	Priors	0.2	0.8	0.2	0.8
		D_1	0.5	-	0.5	-
		D_2	-	-	0.4	-
095	5	Priors	0.1	0.9	0.1	0.9
		D_1	0.4	-	0.4	-
		D_2	-	-	-	0.3
096	6	Priors	0.9	0.1	0.9	0.1
		D_1	0.6	-	0.6	0.2
		D_2	-	-	-	-
097	3	Priors	0.8	0.2	0.8	0.2
		D_1	0.1	-	0.1	-
		D_2	-	-	-	0.1
098	1	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.1	0.2	0.1
		D_2	-	-	-	-
099	5	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.4	-	0.4
		D_2	-	-	0.1	-

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
100	5	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.4	-	0.4
		D_2	-	-	0.8	-
101	6	Priors	0.6	0.4	0.6	0.4
		D_1	0.7	-	0.7	0.8
		D_2	-	-	-	-
102	4	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.9	-	0.9
		D_2	-	-	-	0.4
103	5	Priors	0.7	0.3	0.7	0.3
		D_1	0.9	-	0.9	-
		D_2	-	-	0.2	-
104	2	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.6	0.8	0.6
		D_2	-	-	-	-
105	2	Priors	0.4	0.6	0.4	0.6
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.1
106	6	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.4	-	0.4
		D_2	-	-	-	0.9
107	3	Priors	0.1	0.9	0.1	0.9
		D_1	0.3	-	0.3	-
		D_2	-	-	0.4	-
108	6	Priors	0.6	0.4	0.6	0.4
		D_1	0.2	-	0.2	0.8
		D_2	-	-	-	-
109	3	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.3	0.1	0.3
		D_2	-	-	-	-

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
110	2	Priors	0.7	0.3	0.7	0.3
		D_1	-	0.3	-	0.3
		D_2	-	-	0.4	-
111	6	Priors	0.4	0.6	0.4	0.6
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.6
112	1	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.3	-	0.3
		D_2	-	-	0.6	-
113	2	Priors	0.1	0.9	0.1	0.9
		D_1	-	0.3	-	0.3
		D_2	-	-	-	0.7
114	3	Priors	0.5	0.5	0.5	0.5
		D_1	0.7	-	0.7	-
		D_2	-	-	-	0.9
115	1	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.1	-	0.1
		D_2	-	-	0.6	-
116	6	Priors	0.8	0.2	0.8	0.2
		D_1	0.6	-	0.6	-
		D_2	-	-	-	0.5
117	4	Priors	0.8	0.2	0.8	0.2
		D_1	0.2	-	0.2	0.2
		D_2	-	-	-	-
118	6	Priors	0.6	0.4	0.6	0.4
		D_1	0.2	-	0.2	0.5
		D_2	-	-	-	-
119	5	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.6	-	0.6
		D_2	-	-	-	0.9

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
120	5	Priors	0.4	0.6	0.4	0.6
		D_1	0.8	-	0.8	-
		D_2	-	-	-	0.1
121	6	Priors	0.7	0.3	0.7	0.3
		D_1	0.3	-	0.3	0.8
		D_2	-	-	-	-
122	6	Priors	0.9	0.1	0.9	0.1
		D_1	0.4	-	0.4	0.4
		D_2	-	-	-	-
123	1	Priors	0.3	0.7	0.3	0.7
		D_1	0.4	-	0.4	-
		D_2	-	-	-	0.3
124	5	Priors	0.9	0.1	0.9	0.1
		D_1	0.7	-	0.7	-
		D_2	-	-	0.6	-
125	5	Priors	0.6	0.4	0.6	0.4
		D_1	0.9	-	0.9	-
		D_2	-	-	0.5	-
126	6	Priors	0.5	0.5	0.5	0.5
		D_1	0.3	-	0.3	-
		D_2	-	-	-	0.8
127	1	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.2	-	0.2
		D_2	-	-	-	0.4
128	2	Priors	0.2	0.8	0.2	0.8
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.9
129	5	Priors	0.7	0.3	0.7	0.3
		D_1	0.2	-	0.2	0.3
		D_2	-	-	-	-

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
130	1	Priors	0.9	0.1	0.9	0.1
		D_1	0.4	-	0.4	-
		D_2	-	-	-	0.3
131	6	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.9	-	0.9
		D_2	-	-	0.7	-
132	1	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.9	-	0.9
		D_2	-	-	0.6	-
133	1	Priors	0.6	0.4	0.6	0.4
		D_1	0.1	-	0.1	0.1
		D_2	-	-	-	-
134	5	Priors	0.3	0.7	0.3	0.7
		D_1	0.3	-	0.3	0.8
		D_2	-	-	-	-
135	3	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.6	-	0.6
		D_2	-	-	-	0.5
136	6	Priors	0.4	0.6	0.4	0.6
		D_1	0.2	-	0.2	-
		D_2	-	-	-	0.1
137	2	Priors	0.5	0.5	0.5	0.5
		D_1	-	0.9	0.6	0.9
		D_2	-	-	-	-
138	1	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.5	-	0.5
		D_2	-	-	0.6	-
139	6	Priors	0.4	0.6	0.4	0.6
		D_1	-	0.3	-	0.3
		D_2	-	-	-	0.3

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
140	2	Priors	0.7	0.3	0.7	0.3
		D_1	0.5	-	0.5	-
		D_2	-	-	-	0.5
141	3	Priors	0.5	0.5	0.5	0.5
		D_1	0.4	-	0.4	0.9
		D_2	-	-	-	-
142	5	Priors	0.3	0.7	0.3	0.7
		D_1	-	0.9	-	0.9
		D_2	-	-	-	0.7
143	1	Priors	0.7	0.3	0.7	0.3
		D_1	0.2	-	0.2	0.7
		D_2	-	-	-	-
144	1	Priors	0.6	0.4	0.6	0.4
		D_1	-	0.4	-	0.4
		D_2	-	-	0.3	-
145	2	Priors	0.8	0.2	0.8	0.2
		D_1	0.8	-	0.8	-
		D_2	-	-	-	0.2
146	3	Priors	0.3	0.7	0.3	0.7
		D_1	0.4	-	0.4	-
		D_2	-	-	0.5	-
147	3	Priors	0.8	0.2	0.8	0.2
		D_1	-	0.5	0.8	0.5
		D_2	-	-	-	-
148	2	Priors	0.2	0.8	0.2	0.8
		D_1	-	0.4	-	0.4
		D_2	-	-	-	0.7
149	4	Priors	0.2	0.8	0.2	0.8
		D_1	0.9	-	0.9	-
		D_2	-	-	-	0.5

Appendix Table D2: (Continued)

Participant	Question		Initial table		Selection	
			H_1	H_2	H_1	H_2
150	5	Priors	0.9	0.1	0.9	0.1
		D_1	-	0.4	-	0.4
		D_2	-	-	0.1	-

D.2 Experiment 3: Participant selections

D.2.1 First exercise

Appendix Table D3: Participant selections for the two hypotheses, four diagnostic criteria contingency tables: First exercise

Participant	Question	Initial table		First selection		Second Selection		Third selection	
001	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	-	0.9	-	0.9	-	0.9
		D_2	-	-	0.3	-	0.3	-	0.3
		D_3	-	-	-	0.2	-	0.2	-
002	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	0.8	-	-	0.8	-	0.8	-
		D_2	-	-	0.5	-	0.5	-	0.5
		D_3	-	-	-	0.8	-	0.8	-
003	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	-	0.9	-	0.9	-	0.9
		D_2	-	-	0.5	-	0.5	-	0.5
		D_3	-	-	-	-	0.8	-	0.8
004	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	-	0.9	-	0.9	-	0.9
		D_2	-	-	0.5	-	0.5	-	0.5
		D_3	-	-	-	-	0.8	-	0.8

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
004	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.5	0.5	0.1	0.5	0.1	0.5	0.1
		D_2	-	-	-	0.8	-	0.8	-
		D_3	-	-	-	-	-	0.2	-
005	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	-	0.1	-	0.1	-	0.1
		D_2	-	0.6	-	0.6	-	0.6	-
		D_3	-	-	-	-	0.7	-	0.7
006	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.6	0.6	-	0.6	-	0.6	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
007	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.5	-	0.5	-	0.5
		D_2	-	-	0.1	-	0.1	-	0.1
		D_3	-	-	-	-	0.4	-	0.4
008	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.5	-	0.5	-	0.5
		D_2	-	-	0.1	-	0.1	-	0.1
		D_3	-	-	-	-	0.4	-	0.4

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
016	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.9	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.3	-	0.3	-	0.3	-	0.3
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.3	-	-
017	2	D_4	-	-	-	0.7	0.9	0.7	0.9
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.3	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.6	0.2	0.6	0.2	0.6	0.2
		D_2	-	-	-	-	-	-	-
018	1	D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.3	0.3	0.3
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.3	-	0.3	0.8	0.3	0.8	0.3
019	3	D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.4	-	0.4
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
020	3	D_1	-	0.5	0.7	0.5	0.7	0.5	0.7
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.9	0.9	0.9
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
020	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
			D_1	-	0.9	0.3	0.9	0.3	0.9
			D_2	-	-	-	-	-	-
			D_3	-	-	-	0.8	-	0.8
021	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
			D_1	-	-	0.3	-	0.3	-
			D_2	-	-	0.5	-	0.5	-
			D_3	-	-	-	-	-	-
022	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.3	0.7	0.3	0.7	0.3	0.7	0.3
			D_1	-	0.7	0.9	0.7	0.9	0.7
			D_2	-	-	-	-	-	-
			D_3	-	-	-	-	-	-
023	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.7	0.3	0.7	0.3	0.7	0.3	0.7
			D_1	-	0.8	0.2	0.8	0.2	0.8
			D_2	-	-	-	0.4	-	0.4
			D_3	-	-	-	-	-	-
024	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.7	0.3	0.7	0.3	0.7	0.3	0.7
			D_1	-	0.8	0.2	0.8	0.2	0.8
			D_2	-	-	-	0.4	-	0.4
			D_3	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
024	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.7	0.4	0.7	0.4	0.7	0.4
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.8	-	0.8	0.1
025	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.4	0.4	-	0.4	-	0.4	-
		D_2	-	0.9	-	0.9	-	0.9	-
		D_3	-	-	-	-	0.7	-	0.7
026	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.5	0.5	-	0.5	-	0.5	-
		D_2	-	-	0.1	-	0.1	0.4	0.1
		D_3	-	-	-	-	-	-	-
027	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.4	0.4	0.4	0.4	0.4	0.4	0.4
		D_2	-	-	-	-	0.3	-	0.3
		D_3	-	-	-	-	-	0.7	-
028	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.4	0.4	0.4	0.4	0.4	0.4	0.4
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
032	2	Priors	0.4	0.6	0.4	0.4	0.6	0.4	0.6
		D_1	0.3	-	0.3	0.3	-	0.3	-
		D_2	-	-	-	-	0.2	-	0.2
		D_3	-	-	-	0.3	-	0.3	-
		D_4	-	-	-	-	-	-	0.9
033	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.6	0.4	0.6	0.4	0.6	0.6	0.4
		D_2	0.8	-	0.8	0.1	0.8	0.8	0.1
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.5	0.5	0.2
034	4	Priors	H_1	H_2	H_1	H_2	H_1	H_1	H_2
		D_1	0.6	0.4	0.6	0.4	0.6	0.6	0.4
		D_2	-	0.9	0.8	0.9	0.8	0.8	0.9
		D_3	-	-	-	-	0.2	0.2	0.2
		D_4	-	-	-	-	-	-	-
035	1	Priors	H_1	H_2	H_1	H_2	H_1	H_1	H_2
		D_1	0.3	0.7	0.3	0.7	0.3	0.3	0.7
		D_2	0.2	-	0.2	-	0.2	0.2	-
		D_3	-	-	0.9	-	0.9	0.9	-
		D_4	-	-	-	-	0.2	0.2	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
040	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.3	0.5	0.3	0.5	0.3	0.5
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.2	0.8	0.2
041	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.9	0.5	0.9	0.5	0.9	0.5
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.1	-	0.1	0.9
042	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.6	0.6	-	0.6	-	0.6	-
		D_2	-	0.7	-	0.7	-	0.7	-
		D_3	-	-	-	0.6	-	0.6	-
043	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.3	0.1	0.3	0.1	0.3	0.1
		D_2	-	-	-	0.3	-	0.3	0.9
		D_3	-	-	-	-	-	-	-
044	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.3	0.1	0.3	0.1	0.3	0.1
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
044	3	Priors	0.4	0.6	0.4	0.4	0.6	0.4	0.6
		D_1	-	0.9	-	-	0.9	-	0.9
		D_2	-	-	0.8	-	0.8	-	0.8
		D_3	-	-	-	-	-	-	0.9
		D_4	-	-	-	-	0.3	-	0.3
045	6	Priors	H_1	H_2	H_1	H_1	H_2	H_1	H_2
			0.6	0.4	0.6	0.6	0.4	0.6	0.4
		D_1	-	0.1	-	-	0.1	-	0.1
		D_2	-	-	-	-	0.6	-	0.6
		D_3	-	-	-	-	0.6	-	0.6
		D_4	-	-	-	-	-	-	0.6
046	5	Priors	H_1	H_2	H_1	H_1	H_2	H_1	H_2
			0.3	0.7	0.3	0.3	0.7	0.3	0.7
		D_1	0.9	-	0.9	0.9	0.9	0.9	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.4	-	0.4	0.6
		D_4	-	-	-	-	-	-	-
047	6	Priors	H_1	H_2	H_1	H_1	H_2	H_1	H_2
			0.2	0.8	0.2	0.2	0.8	0.2	0.8
		D_1	-	0.4	-	0.8	0.4	0.8	0.4
		D_2	-	-	-	-	-	-	0.9
		D_3	-	-	-	-	0.3	-	0.3
		D_4	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
060	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	0.1	0.1	-	0.1	-	0.1	-
		D_2	-	0.5	-	0.5	-	0.5	-
		D_3	-	-	-	0.2	-	0.2	-
		D_4	-	-	-	-	-	0.7	-
061	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	0.8	0.7	0.8	0.7	0.8	0.7
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.9	-	0.9
		D_4	-	-	-	-	-	0.4	-
062	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.4	0.4	-	0.4	-	0.4	-
		D_2	-	-	0.7	-	0.7	-	0.7
		D_3	-	-	-	0.7	-	0.7	0.1
		D_4	-	-	-	-	-	-	-
063	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	0.4	0.4	0.4	0.4	0.4	0.4
		D_2	-	-	-	0.6	-	0.6	-
		D_3	-	-	-	-	-	0.8	-
		D_4	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
064	4	Priors	0.4	0.6	0.4	0.4	0.6	0.4	0.6
		D_1	0.3	-	0.3	0.3	-	0.3	0.3
		D_2	-	-	0.8	0.8	0.9	0.8	0.9
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
065	3	Priors	0.3	0.7	0.3	0.3	0.7	0.3	0.7
		D_1	-	0.1	-	-	0.1	-	0.1
		D_2	-	-	0.4	0.4	-	0.4	-
		D_3	-	-	-	0.5	-	0.5	-
		D_4	-	-	-	-	-	-	0.1
066	3	Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	0.2	-	-	0.2	-	0.2
		D_2	-	-	-	-	-	-	-
		D_3	-	-	0.8	0.8	0.6	0.8	0.6
		D_4	-	-	-	-	-	0.4	-
067	2	Priors	0.9	0.1	0.9	0.9	0.1	0.9	0.1
		D_1	0.4	-	0.4	0.4	-	0.4	-
		D_2	-	-	-	-	-	-	0.8
		D_3	-	-	0.1	0.1	0.4	0.1	0.4
		D_4	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
068	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.2	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	0.2	-	0.2	-	0.2	-
		D_2	-	-	-	0.7	-	0.7	-
		D_3	-	-	-	-	-	0.7	-
069	4	D_4	-	-	-	-	-	0.2	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.3	-	0.3	0.6	0.3	0.6	0.3
		D_2	-	-	-	-	-	0.9	-
070	3	D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.2	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.6	-	0.6	-	0.6	-	0.6
071	6	D_2	-	-	0.8	-	0.8	-	0.8
		D_3	-	-	-	-	0.1	-	0.1
		D_4	-	-	-	-	-	-	0.7
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
071	6	D_1	-	0.6	0.9	0.6	0.9	0.6	0.9
		D_2	-	-	-	-	0.8	-	0.8
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
072	2	Priors	0.4	0.6	0.4	0.6	0.4	0.4	0.6
		D_1	0.2	-	0.2	-	0.2	0.2	0.4
		D_2	-	-	0.9	-	0.9	-	0.9
		D_3	-	-	-	-	0.6	-	0.6
		D_4	-	-	-	-	-	-	-
073	2	Priors	0.8	0.2	0.8	0.2	0.8	0.8	0.2
		D_1	-	0.1	-	0.1	-	-	0.1
		D_2	-	-	-	-	0.2	0.2	-
		D_3	-	-	-	0.6	-	-	0.6
		D_4	-	-	-	-	-	-	0.9
074	6	Priors	0.4	0.6	0.4	0.6	0.4	0.4	0.6
		D_1	0.2	-	0.2	0.4	0.2	0.2	0.4
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.4	0.4	0.5
		D_4	-	-	-	-	-	-	-
075	2	Priors	0.1	0.9	0.1	0.9	0.1	0.1	0.9
		D_1	0.1	-	0.1	-	0.1	0.1	-
		D_2	-	-	0.3	-	0.3	0.3	-
		D_3	-	-	-	-	0.9	0.9	-
		D_4	-	-	-	-	-	-	0.7

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
076	5	Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.2	0.2	-	0.2	-	0.2	0.9
		D_2	-	0.7	-	0.7	0.6	0.7	0.6
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
077	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.8	0.2	0.8	0.2	0.8	0.2	0.2
		D_2	0.6	-	0.6	-	0.6	-	-
		D_3	-	-	-	-	0.6	-	0.6
		D_4	-	-	-	-	0.7	-	0.7
078	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.3	0.7	0.3	0.7	0.3	0.3	0.7
		D_2	0.9	-	0.9	-	0.9	0.9	-
		D_3	-	-	-	0.7	-	-	0.7
		D_4	-	-	-	-	0.4	0.4	-
079	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.7	0.3	0.7	0.3	0.7	0.7	0.3
		D_2	-	0.6	-	0.6	-	-	0.6
		D_3	-	-	-	0.8	-	-	0.8
		D_4	-	-	-	-	0.4	-	0.4
			-	-	-	-	-	0.8	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
084	2	Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.4	0.4	-	0.4	-	0.4	-
		D_2	-	-	0.8	-	0.8	-	0.8
		D_3	-	-	-	0.7	-	0.7	-
		D_4	-	-	-	-	-	-	0.1
085	5	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.6	-	0.6	-	0.6
		D_2	-	0.4	-	0.4	-	0.4	-
		D_3	-	-	-	-	0.5	-	0.5
		D_4	-	-	-	-	-	0.9	-
086	3	Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.2	0.2	-	0.2	-	0.2	-
		D_2	-	-	0.7	-	0.7	-	0.7
		D_3	-	-	-	0.2	-	0.2	-
		D_4	-	-	-	-	-	-	0.4
087	6	Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	-	0.6	-	0.6	-	0.6
		D_2	-	-	0.2	-	0.2	-	0.2
		D_3	-	-	-	-	0.7	-	0.7
		D_4	-	-	-	-	-	-	0.4

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
092	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	0.8	0.7	0.8	0.7	0.8	0.7
		D_2	-	-	-	-	-	-	0.6
		D_3	-	-	-	0.3	-	0.3	-
093	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	0.5	0.1	0.5	0.1	0.5	0.1
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.1	0.8	0.1
094	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	0.6	0.3	0.6	0.3	0.6	0.3
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.2	-	0.2	0.3
095	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	-	-	0.1	-	0.1	-	0.1
		D_2	-	-	0.3	-	0.3	-	0.3
		D_3	-	-	-	-	0.3	-	0.3
096	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	-	-	0.1	-	0.1	-	0.1
		D_2	-	-	0.3	-	0.3	-	0.3
		D_3	-	-	-	-	0.3	-	0.3

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
100	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.5	0.5	0.8	0.5	0.8	0.5	0.8
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.2	0.3	0.2
101	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	-	0.2	-	0.2	0.4	0.2
		D_2	-	-	-	-	-	-	-
		D_3	-	0.9	-	0.9	0.8	0.9	0.8
102	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	0.3	0.3	-	0.3	0.2	0.3	0.2
		D_2	-	0.4	-	0.4	-	0.4	0.7
		D_3	-	-	-	-	-	-	-
103	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	0.3	0.1	0.3	0.1	0.3	0.1
		D_2	-	-	-	0.2	-	0.2	0.6
		D_3	-	-	-	-	-	-	-
104	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	0.3	0.1	0.3	0.1	0.3	0.1
		D_2	-	-	-	0.2	-	0.2	0.6
		D_3	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
104	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	0.8	0.8	0.5	0.8	0.5	0.8	0.5
		D_2	-	-	-	0.6	-	0.6	0.2
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
105	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	-	0.5	-	0.5	-	0.5
		D_2	-	0.5	-	0.5	-	0.5	-
		D_3	-	-	-	0.9	-	0.9	-
		D_4	-	-	-	-	-	0.3	-
106	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	0.3	0.3	-	0.3	-	0.3	-
		D_2	-	-	-	-	-	-	-
		D_3	-	-	0.1	-	0.1	-	0.1
		D_4	-	-	-	0.7	-	0.7	0.8
107	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	0.3	0.3	0.9	0.3	0.9	0.3
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.9	-	0.9	0.6
		D_4	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
108	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	-	0.3	-	0.3	0.1	0.3
		D_2	-	-	-	-	-	-	-
		D_3	-	0.5	-	0.5	0.4	0.5	0.4
		D_4	-	-	-	-	-	-	-
109	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	0.9	0.9	-	0.9	-	0.9	-
		D_2	-	-	0.3	-	0.3	-	0.3
		D_3	-	-	-	0.2	-	0.2	-
		D_4	-	-	-	-	-	0.1	-
110	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	0.9	0.9	0.5	0.9	0.5	0.9	0.5
		D_2	-	-	-	0.6	-	0.6	0.2
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
111	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.9	0.2	0.9	0.2	0.9	0.2
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.1	-	0.1	0.4
		D_4	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
112	4	Priors	0.2	0.8	0.2	0.8	0.2	0.2	0.8
		D_1	0.1	-	0.1	0.2	0.1	0.1	0.2
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.2	-	0.2	-
		D_4	-	-	-	-	-	-	0.2
113	5	Priors	H_1	H_2	H_1	H_2	H_1	H_1	H_2
		D_1	0.3	0.7	0.3	0.7	0.3	0.3	0.7
		D_2	0.4	-	0.4	0.5	0.4	0.4	0.5
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.1	0.1	0.7
114	5	Priors	H_1	H_2	H_1	H_2	H_1	H_1	H_2
		D_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_2	-	0.6	-	0.6	-	-	0.6
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	0.6	0.3	0.3	0.6
115	5	Priors	H_1	H_2	H_1	H_2	H_1	H_1	H_2
		D_1	0.9	0.1	0.9	0.1	0.9	0.9	0.1
		D_2	0.8	-	0.8	-	0.8	0.8	-
		D_3	-	-	0.6	-	0.6	0.6	-
		D_4	-	-	-	-	0.3	0.3	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
116	3	Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	-	0.6	-	0.6	0.2	0.6
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	0.2	0.6	0.2	0.6	0.2
117	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.6	0.4	0.6	0.4	0.6	0.6	0.4
		D_2	-	0.1	-	0.1	-	-	0.1
		D_3	-	-	0.6	-	0.6	0.6	0.2
		D_4	-	-	-	-	-	0.9	-
118	2	Priors	H_1	H_2	H_1	H_2	H_1	H_1	H_2
		D_1	0.8	0.2	0.8	0.2	0.8	0.8	0.2
		D_2	-	0.7	0.7	0.7	0.7	0.7	0.7
		D_3	-	-	-	0.3	-	0.3	0.3
		D_4	-	-	-	-	-	-	-
119	6	Priors	H_1	H_2	H_1	H_2	H_1	H_1	H_2
		D_1	0.1	0.9	0.1	0.9	0.1	0.1	0.9
		D_2	-	-	-	0.5	-	0.9	0.5
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.1	0.8	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
120	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	0.9	-	0.9	-	0.9	-
		D_2	-	-	0.1	0.4	0.1	0.4	0.1
		D_3	-	-	-	-	-	-	-
121	4	D_4	-	-	-	-	0.7	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.3	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.2	0.6	0.2	0.6	0.2	0.6
		D_2	-	-	-	-	-	-	-
122	2	D_3	-	-	-	-	0.1	0.6	0.1
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	0.5	-	0.5	-	0.5	-
123	5	D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.4	0.3	0.4	0.3
		D_4	-	-	-	0.7	-	0.7	0.7
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.9	0.1	0.9	0.1	0.9	0.1	0.9
123	5	D_1	-	0.1	-	0.1	-	0.1	-
		D_2	-	-	0.9	-	0.9	-	0.9
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	0.7	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
124	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.4	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.7	-	0.7	-	0.7	-
		D_2	-	-	0.5	-	0.5	-	0.5
		D_3	-	-	-	0.3	0.3	-	0.3
125	4	D_4	-	-	-	-	0.1	-	0.1
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.2	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	0.3	-	0.3	-	0.3	-
		D_2	-	-	0.3	-	0.3	-	0.3
126	5	D_3	-	-	-	0.8	0.8	-	0.8
		D_4	-	-	-	-	0.2	-	0.2
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	0.8	-	0.8	-	0.8	-
127	2	D_2	-	-	-	0.4	-	0.4	-
		D_3	-	-	-	-	0.2	-	0.2
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
128	3	D_1	0.9	-	0.9	-	0.9	-	0.9
		D_2	-	-	-	-	0.1	-	0.1
		D_3	-	-	-	-	0.5	-	0.5
		D_4	-	-	0.5	-	0.5	-	0.5
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
128	4	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.8	-	0.8	-	0.8
		D_2	-	-	0.8	-	0.8	-	0.8
		D_3	-	-	-	-	0.9	-	0.9
		D_4	-	-	-	-	-	-	0.8
129	2	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.9	-	0.9	-	0.9
		D_2	-	0.2	-	0.2	0.7	0.2	0.7
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	0.1
130	6	Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	0.5	0.7	0.5	0.7	0.5	0.7
		D_2	-	-	-	-	0.8	0.6	0.8
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
131	1	Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	0.6	0.6	-	0.6	-	0.6	-
		D_2	-	-	0.5	-	0.5	-	0.5
		D_3	-	-	-	0.4	-	0.4	-
		D_4	-	-	-	-	-	-	0.9

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
132	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	0.4	0.4	-	0.4	-	0.4	-
		D_2	-	-	0.1	0.2	0.1	0.2	0.1
		D_3	-	-	-	-	-	0.8	-
		D_4	-	-	-	-	-	-	-
133	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	0.5	0.4	0.5	0.4	0.5	0.4
		D_2	-	-	-	0.2	-	0.2	0.7
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
134	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	-	0.6	-	0.6	-	0.6
		D_2	-	0.2	-	0.2	-	0.2	-
		D_3	-	-	-	0.3	-	0.3	-
		D_4	-	-	-	-	-	-	0.9
135	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	0.1	0.1	-	0.1	-	0.1	-
		D_2	-	-	0.3	-	0.3	-	0.3
		D_3	-	-	-	-	0.2	-	0.2
		D_4	-	-	-	-	-	-	0.2

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
136	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	-	0.5	-	0.5	-	0.5	-
		D_2	-	-	-	0.9	-	0.9	-
		D_3	-	-	-	-	-	0.4	-
		D_4	-	-	-	-	-	0.8	-
137	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.9	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.6	-	0.6	-	0.6	-	0.6
		D_2	-	-	-	0.6	-	0.6	-
		D_3	-	-	-	-	0.8	-	0.8
		D_4	-	-	-	-	-	-	0.5
138	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.9	-	0.9	-	0.9	-	0.9
		D_2	-	-	-	0.3	0.3	0.3	0.3
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	0.4
139	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.9	-	0.9	-	0.9	-	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	0.5	-	0.5	0.8	0.5

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
140	6	Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	-	0.6	-	0.6	-	0.6
		D_2	-	-	-	-	-	0.2	-
		D_3	-	0.8	-	0.8	-	0.8	-
		D_4	-	-	-	0.9	-	0.9	-
141	6	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.2	-	0.2	0.6	0.2
		D_2	-	-	-	-	-	-	-
		D_3	-	0.4	-	0.4	0.4	0.4	0.4
		D_4	-	-	-	-	-	-	-
142	2	Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.7	0.7	0.4	0.7	0.4	0.7	0.4
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.1	-	0.1	0.6
		D_4	-	-	-	-	-	-	-
143	4	Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	0.8	0.6	0.8	0.6	0.8	0.6
		D_2	-	-	-	0.1	-	0.1	-
		D_3	-	-	-	-	-	-	0.3
		D_4	-	-	-	-	-	-	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
144	3	Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.8	0.8	0.8	0.8	0.8	0.8	0.8
		D_2	-	-	-	0.9	-	0.9	0.1
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
145	1	Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	0.7	0.2	0.7	0.2	0.7	0.2
		D_2	-	-	-	0.8	-	0.8	0.3
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
146	4	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	0.4	0.4	-	0.4	-	0.4
		D_2	-	-	0.3	0.2	0.3	0.2	0.3
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	0.6
147	4	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.3	0.3	0.1	0.3	0.1	0.3	0.1
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	0.5
		D_4	-	-	-	0.6	-	0.6	-

Appendix Table D3: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection			
148	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2	
			0.1	0.9	0.1	0.9	0.1	0.9	0.1	0.9	
			D_1	-	0.4	0.2	0.4	0.2	0.4	0.2	
			D_2	-	-	-	-	-	-	-	
			D_3	-	-	-	-	-	-	-	
		D_4	-	-	-	-	0.8	-	0.8	0.3	
149	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2	
			0.5	0.5	0.5	0.5	0.5	0.5	0.5	0.5	
			D_1	-	0.8	-	0.8	-	0.8	-	0.8
			D_2	-	-	0.1	-	0.1	-	0.1	-
			D_3	-	-	-	-	-	0.9	-	0.9
		D_4	-	-	-	-	-	-	0.7		
150	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2	
			0.6	0.4	0.6	0.4	0.6	0.4	0.6	0.4	
			D_1	0.1	-	0.1	-	0.1	-	0.1	-
			D_2	-	-	0.4	-	0.4	0.9	0.4	0.9
			D_3	-	-	-	-	-	-	-	0.9
		D_4	-	-	-	-	-	-	-		

D.2.2 Second exercise

Appendix Table D4: Participant selections for the two hypotheses, four diagnostic criteria contingency tables: Second exercise

Participant	Question	Initial table		First selection		Second Selection		Third selection	
001	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.2	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.2	-	0.2	-	0.2	-	0.2
		D_2	-	-	-	0.1	-	0.1	-
		D_3	-	-	-	-	0.8	-	0.8
002	2	D_4	-	-	-	-	-	-	0.7
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	0.2	0.3	0.2	0.3	0.2	0.3
		D_2	-	-	-	-	-	-	-
003	3	D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.2	-	0.2
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.9	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.3	-	0.3	-	0.3	-	0.3
		D_2	-	-	-	0.5	-	0.5	-
		D_3	-	-	-	-	0.3	-	0.3
		D_4	-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
008	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.3	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.2	-	0.2	-	0.2	-
		D_2	-	-	0.8	-	0.8	-	-
		D_3	-	-	-	-	-	0.3	-
009	5	D_4	-	-	-	-	0.4	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	0.8	0.4	0.8	0.4	0.8	0.8
		D_2	-	-	-	-	-	-	-
010	2	D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.1	0.9	0.9
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.4	0.6	0.4	0.6	0.4	0.6	0.6
		D_1	-	0.5	0.6	0.5	0.6	0.5	0.5
011	1	D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.8	-	0.6
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.2	0.8	0.2	0.8	0.2	0.8	0.8
		D_1	-	0.6	0.3	0.6	0.3	0.6	0.6
		D_2	-	-	-	-	0.9	-	0.2
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
			-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
012	1	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.3	-	0.3	-	0.3
		D_2	-	0.6	-	0.6	-	0.6	-
		D_3	-	-	-	0.7	-	0.7	-
		D_4	-	-	-	-	-	0.2	-
013	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.4	0.6	0.4	0.6	0.4	0.6	0.6
		D_2	0.2	-	0.2	0.5	0.2	0.2	0.5
		D_3	-	-	-	-	-	-	0.9
		D_4	-	-	-	-	-	-	0.3
014	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.9	0.1	0.9	0.1	0.9	0.1	0.1
		D_2	-	0.6	0.1	0.6	0.1	0.1	0.6
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	0.7	-
015	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.9	0.1	0.9	0.1	0.9	0.1	0.1
		D_2	-	0.6	-	0.6	0.3	0.3	0.6
		D_3	-	-	0.1	-	0.1	0.1	0.1
		D_4	-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
016	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.7	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	0.8	-	0.8	-	0.8	-
		D_2	-	-	0.9	-	0.9	-	-
		D_3	-	-	-	0.5	0.5	0.7	-
017	1	D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.1	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	0.7	-	0.7	0.4	0.7	0.4	0.7
		D_2	-	-	-	-	-	-	-
018	3	D_3	-	-	-	-	-	0.7	0.7
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	0.1	0.8	0.1	0.8	0.1	0.8
019	6	D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.8	0.8	0.8
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
019	6	D_1	0.8	-	0.8	-	0.8	-	0.8
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.3	-	-
		D_4	-	-	-	0.8	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
020	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	-	0.6	0.1	0.6	0.1	0.6
		D_2	-	-	0.8	-	0.8	0.7	0.8
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
021	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	0.5	0.5	-	0.5	-	0.5	-
		D_2	-	0.8	-	0.8	-	0.8	-
		D_3	-	-	-	0.8	-	0.8	-
		D_4	-	-	-	-	-	0.8	-
022	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	0.5	0.5	-	0.5	-	0.5	-
		D_2	-	-	0.9	-	0.9	-	0.9
		D_3	-	-	-	0.7	-	0.7	-
		D_4	-	-	-	-	-	-	0.6
023	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.6	0.6	-	0.6	-	0.6	-
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	0.2
		D_4	-	0.8	-	0.8	0.9	0.8	0.9

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
028	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	0.4	0.4	-	0.4	-	0.4	0.3
		D_2	-	-	0.2	0.3	0.2	0.3	0.2
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
029	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	-	0.7	-	0.7	-	0.7
		D_2	-	-	-	0.9	-	0.9	-
		D_3	-	-	0.9	-	0.9	-	0.9
		D_4	-	-	-	-	-	0.3	-
030	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	-	0.8	0.2	0.8	0.2	0.8	0.2
		D_2	-	-	-	-	0.5	-	0.5
		D_3	-	-	-	-	-	-	0.1
		D_4	-	-	-	-	-	-	-
031	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.3	-	0.3	-	0.3
		D_2	-	0.3	-	0.3	-	0.3	-
		D_3	-	-	-	0.9	-	0.9	-
		D_4	-	-	-	-	-	0.6	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
032	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	-	0.9	-	0.9	-	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	0.1	-	0.1	-	0.1
033	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	0.6	0.6	0.6	0.6	0.6	0.6
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.8	-	0.8	0.8
034	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.8	-	0.8	0.8	0.8	0.8	0.8
		D_2	-	-	-	0.3	-	0.3	0.5
		D_3	-	-	-	-	-	-	-
035	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.9	0.6	0.9	0.6	0.9	0.6
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.4	-	0.4	0.7
036	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.9	0.6	0.9	0.6	0.9	0.6
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.4	-	0.4	0.7

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
040	4		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.3	0.7	0.3	0.7	0.3	0.7	
		D_1	0.6	-	0.6	0.2	0.6	0.2	
		D_2	-	-	-	-	-	-	
		D_3	-	-	-	-	-	-	
041	1		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.4	0.6	0.4	0.6	0.4	0.6	
		D_1	0.5	-	0.5	0.4	0.5	0.4	
		D_2	-	-	-	-	-	-	
		D_3	-	-	-	-	0.5	0.4	
042	2		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	
		D_1	-	0.2	0.7	0.2	0.7	0.2	
		D_2	-	-	-	-	0.3	-	
		D_3	-	-	-	-	-	0.6	
043	5		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.3	0.7	0.3	0.7	0.3	0.7	
		D_1	0.7	-	0.7	-	0.7	-	
		D_2	-	-	0.8	-	0.8	-	
		D_3	-	-	-	-	0.1	-	
044	6		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.3	0.7	0.3	0.7	0.3	0.7	
		D_1	0.7	-	0.7	-	0.7	-	
		D_2	-	-	0.8	-	0.8	-	
		D_3	-	-	-	-	0.1	-	

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
044	6		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.6	0.4	0.6	0.4	0.6	0.4	
		D_1	0.4	-	0.4	-	0.4	-	
		D_2	-	-	-	0.4	-	0.4	
		D_3	-	-	-	-	0.6	-	
045	2		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.6	0.4	0.6	0.4	0.6	0.4	
		D_1	0.2	-	0.2	0.3	0.2	0.3	
		D_2	-	-	-	-	-	-	
		D_3	-	-	-	-	-	0.6	
046	2		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.1	0.9	0.1	0.9	0.1	0.9	
		D_1	-	0.8	0.9	0.8	0.9	0.8	
		D_2	-	-	-	-	0.4	0.1	
		D_3	-	-	-	-	-	-	
047	3		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.3	0.7	0.3	0.7	0.3	0.7	
		D_1	0.6	-	0.6	-	0.6	-	
		D_2	-	-	0.5	0.3	0.5	0.3	
		D_3	-	-	-	-	-	-	
048	3		H_1	H_2	H_1	H_2	H_1	H_2	
		Priors	0.3	0.7	0.3	0.7	0.3	0.7	
		D_1	0.6	-	0.6	-	0.6	-	
		D_2	-	-	0.5	0.3	0.5	0.3	
		D_3	-	-	-	-	-	-	

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
052	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.1	0.5	0.1	0.5	0.1	0.5
		D_2	-	-	-	0.3	-	0.3	0.6
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
053	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	-	0.4	-	0.4	-	0.4
		D_2	-	-	0.4	-	0.4	-	0.4
		D_3	-	-	-	-	0.2	-	0.2
		D_4	-	-	-	-	-	-	0.7
054	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.3	0.3	0.4	0.3	0.4	0.3	0.4
		D_2	-	-	-	0.7	-	0.7	0.5
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
055	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	0.3	0.3	0.4	0.3	0.4	0.3	0.4
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.3	-	0.3	0.2
		D_4	-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
056	6	Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	-	0.3	-	0.3	-	0.3
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.9	0.9	0.9
		D_4	-	0.9	-	0.9	-	0.9	-
057	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.9	0.1	0.9	0.1	0.9	0.1	0.1
		D_2	0.8	-	0.8	-	0.8	0.8	0.5
		D_3	-	-	-	-	-	-	-
		D_4	-	0.3	-	0.3	0.8	0.3	0.8
058	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.8	0.2	0.8	0.2	0.8	0.8	0.2
		D_2	0.8	-	0.8	0.9	0.8	0.8	0.9
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.9	0.9	0.1
059	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.1	0.9	0.1	0.9	0.1	0.1	0.9
		D_2	0.1	-	0.1	0.5	0.1	0.1	0.5
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	0.2	0.3

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
064	1	Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	0.8	0.3	0.8	0.3	0.8	0.3
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	0.1	-	0.1	0.9
065	4	Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_2	-	-	-	0.5	-	0.5	-
		D_3	-	-	-	-	-	-	0.4
		D_4	-	-	-	-	-	-	-
066	2	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.8	0.8	0.4	0.8	0.4	0.8	0.4
		D_2	-	-	-	0.1	-	0.1	0.1
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
067	3	Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	-	0.9	-	0.9	0.6	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.8	-	0.8	-
		D_4	-	-	-	-	0.4	-	0.4

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
068	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	0.1	0.1	-	0.1	-	0.1	-
		D_2	-	-	-	-	-	0.5	-
		D_3	-	-	0.3	-	0.3	-	0.3
		D_4	-	-	-	0.9	-	0.9	-
069	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.5	0.7	0.5	0.7	0.5	0.7
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.8	-	0.8	-
		D_4	-	-	-	-	-	-	0.8
070	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	-	0.1	-	0.1	-	0.1
		D_2	-	-	0.7	-	0.7	-	0.7
		D_3	-	-	-	-	0.3	-	0.3
		D_4	-	-	-	-	-	-	0.4
071	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	0.6	0.6	0.5	0.6	0.5	0.6	0.5
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	0.6	-
		D_4	-	-	-	0.8	-	0.8	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
072	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	-	-	0.6	-	0.6	-	0.6
		D_2	-	0.6	-	0.6	-	0.6	-
		D_3	-	-	-	-	0.2	-	0.2
073	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.7	0.7	-	0.7	0.7	0.7	0.7
		D_2	-	-	0.4	-	0.4	0.1	0.4
		D_3	-	-	-	-	-	-	-
074	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.9	0.2	0.9	0.2	0.9	0.2
		D_2	-	-	-	0.3	-	0.3	0.6
		D_3	-	-	-	-	-	-	-
075	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	-	-	0.9	-	0.9	-	0.9
		D_2	-	-	-	-	0.2	-	0.2
		D_3	-	-	0.5	-	0.5	-	0.5
076	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	-	-	0.9	-	0.9	-	0.9
		D_2	-	-	-	-	0.2	-	0.2
		D_3	-	-	0.5	-	0.5	-	0.5

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
076	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.1	-	0.1	-	0.1
		D_2	-	0.8	-	0.8	0.8	0.8	0.8
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	0.9	-
077	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.3	0.9	0.3	0.9	0.3	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	0.4
		D_4	-	-	-	-	0.6	-	0.6
078	6	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.3	-	0.3	0.8	0.3
		D_2	-	0.1	-	0.1	0.5	0.1	0.5
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
079	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.4	0.4	-	0.4	0.4	0.4	0.4
		D_2	-	-	-	-	-	-	-
		D_3	-	-	0.7	-	0.7	-	0.7
		D_4	-	-	-	-	-	0.2	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
080	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	0.7	0.7	-	0.7	-	0.7	-
		D_2	-	-	0.9	-	0.9	-	0.9
		D_3	-	-	-	-	-	0.9	-
081	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	-	0.2	0.5	0.2	0.5	0.2	0.5
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.3	-	0.3	0.7
082	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.2	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.6	0.6	-	0.6	-	0.6	-
		D_2	-	0.5	-	0.5	-	0.5	-
		D_3	-	-	-	-	0.2	-	0.2
083	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.1	0.1	-	0.1	-	0.1	-
		D_2	-	0.2	-	0.2	-	0.2	-
		D_3	-	-	-	0.9	-	0.9	-
084	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.1	0.1	-	0.1	-	0.1	-
		D_2	-	0.2	-	0.2	-	0.2	-
		D_3	-	-	-	0.9	-	0.9	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
084	Priors	0.8	0.2	0.8	0.2	0.8	0.2	0.8	0.2
	D_1	-	0.3	-	0.3	-	0.3	-	0.3
	D_2	-	-	0.2	-	0.2	-	0.2	-
	D_3	-	-	-	-	-	0.9	-	0.9
	D_4	-	-	-	-	-	-	-	0.8
085	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
	D_1	0.8	0.2	0.8	0.2	0.8	0.2	0.8	0.2
	D_2	0.3	-	0.3	0.4	0.3	0.4	0.3	0.4
	D_3	-	-	-	-	-	-	-	-
	D_4	-	-	-	-	0.9	-	0.9	0.1
086	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
	D_1	0.3	0.7	0.3	0.7	0.3	0.7	0.3	0.7
	D_2	-	0.9	-	0.9	-	0.9	-	0.9
	D_3	-	-	0.5	-	0.5	-	0.5	-
	D_4	-	-	-	-	-	0.3	-	0.3
087	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
	D_1	0.4	0.6	0.4	0.6	0.4	0.6	0.4	0.6
	D_2	0.3	-	0.3	0.4	0.3	0.4	0.3	0.4
	D_3	-	-	-	-	-	-	-	-
	D_4	-	-	-	-	0.8	-	0.8	0.2

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
092	6	Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	0.7	0.7	-	0.7	-	0.7	-
		D_2	-	-	-	-	-	-	0.9
		D_3	-	-	-	0.3	-	0.3	-
		D_4	-	-	0.5	-	0.5	-	0.5
093	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.2	0.8	0.2	0.8	0.2	0.8	0.8
		D_2	0.7	-	0.7	0.2	0.7	0.7	0.2
		D_3	-	-	-	-	0.1	0.1	0.9
		D_4	-	-	-	-	-	-	-
094	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_2	0.7	-	0.7	-	0.7	0.7	-
		D_3	-	-	-	0.7	-	-	0.7
		D_4	-	-	-	-	0.6	0.6	-
095	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.6	0.4	0.6	0.4	0.6	0.6	0.4
		D_2	0.3	-	0.3	-	0.3	0.3	-
		D_3	-	-	0.9	-	0.9	0.9	-
		D_4	-	-	-	-	0.4	0.4	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
096	1	Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.5	0.5	0.6	0.5	0.6	0.5	0.6
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.4	-	0.4	-
		D_4	-	-	-	-	-	-	0.2
097	2	Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	0.6	0.6	0.7	0.6	0.7	0.6	0.7
		D_2	-	-	-	-	0.7	-	0.7
		D_3	-	-	-	-	-	-	0.8
		D_4	-	-	-	-	-	-	-
098	4	Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	-	0.7	-	0.7	0.2	0.7
		D_2	-	0.9	-	0.9	-	0.9	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	0.5	-	0.5	-
099	2	Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	0.4	0.7	0.4	0.7	0.4	0.7
		D_2	-	-	-	0.2	-	0.2	0.3
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
100	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.7	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	0.2	-	0.2	-	0.2	0.4
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
101	5	D_4	-	-	0.8	-	0.8	0.7	0.8
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.9	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.5	-	0.5	-	0.5	0.9	0.5
		D_2	-	-	0.7	-	0.7	0.5	-
102	1	D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	0.3	0.3	0.3	0.3	0.3	0.3
103	6	D_2	-	-	-	-	0.9	0.2	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.2	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.6	-	0.6	0.9	0.6	0.9	0.6
		D_2	-	-	-	-	-	0.1	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.8	-	-
			-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
104	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.9	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	-	-	0.7	-	0.7	0.4	0.7
		D_2	-	-	-	-	-	-	-
		D_3	-	0.4	-	0.4	0.5	0.4	0.5
105	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	0.4	0.4	-	0.4	-	0.4	-
		D_2	-	0.8	-	0.8	-	0.8	-
		D_3	-	-	-	0.9	-	0.9	-
106	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	-	0.5	-	0.5	-	0.5
		D_2	-	0.4	-	0.4	-	0.4	-
		D_3	-	-	-	-	0.2	-	0.2
107	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.3	0.3	0.1	0.3	0.1	0.3	0.1
		D_2	-	-	-	0.4	-	0.4	-
		D_3	-	-	-	-	-	0.2	-
108	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.4	0.4	0.4	0.4	0.4
		D_1	-	-	-	-	-	-	-
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
108	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	0.9	0.9	0.4	0.9	0.4	0.9	0.4
		D_2	-	-	-	0.5	-	0.5	0.3
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
109	5	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.8	0.8	0.2	0.8	0.2	0.8	0.2
		D_1	-	-	0.7	-	0.7	-	0.7
		D_2	-	0.9	-	0.9	-	0.9	-
		D_3	-	-	-	0.2	-	0.2	-
		D_4	-	-	-	-	-	0.9	-
110	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.3	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	-	0.4	-	0.4	-	0.4
		D_2	-	-	-	0.7	-	0.7	0.1
		D_3	-	-	-	-	-	-	-
		D_4	-	-	0.6	-	0.6	-	0.6
111	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_1	0.6	0.6	0.3	0.6	0.3	0.6	0.3
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.3	-	0.3	0.4
		D_4	-	-	-	-	-	-	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
112	2	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	0.3	0.9	0.3	0.9	0.3	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-
113	4	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	0.8	0.7	0.8	0.7	0.8	0.7
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.3	-	0.3	-
114	1	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.1	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.2	0.2	0.7	0.2	0.7	0.2	0.7
		D_2	-	-	-	-	0.5	0.5	0.5
		D_3	-	-	-	-	-	-	-
115	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	-	0.7	-	0.7	-	0.7
		D_2	-	-	-	-	0.1	-	0.1
		D_3	-	-	-	-	-	-	0.4
116	3	H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
		Priors	0.4	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	-	-	0.7	-	0.7	-	0.7
		D_2	-	-	-	-	0.1	-	0.1
		D_3	-	-	-	-	-	-	0.4

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
116	1	Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	0.7	0.7	0.4	0.7	0.4	0.7	0.4
		D_2	-	-	-	0.9	-	0.9	0.9
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
117	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.8	0.2	0.8	0.2	0.8	0.2	0.2
		D_2	0.5	0.7	0.5	0.7	0.5	0.7	0.7
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
118	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.3	0.7	0.3	0.7	0.3	0.7	0.7
		D_2	0.1	-	0.1	0.8	0.1	0.1	0.8
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.3	0.3	0.5
119	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.4	0.6	0.4	0.6	0.4	0.4	0.6
		D_2	-	0.9	-	0.9	-	-	0.9
		D_3	-	-	-	-	-	-	-
		D_4	-	-	0.7	0.5	0.7	0.7	0.5
			-	-	-	-	-	0.6	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
120	6	Priors	0.6	0.4	0.6	0.6	0.4	0.6	0.4
		D_1	0.8	-	0.8	0.8	-	0.8	-
		D_2	-	-	-	-	0.8	-	0.8
		D_3	-	-	0.4	0.4	-	0.4	-
		D_4	-	-	-	-	-	-	0.2
121	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.4	0.6	0.4	0.6	0.4	0.6	0.6
		D_2	0.7	-	0.7	0.2	0.7	0.2	0.2
		D_3	-	-	-	-	0.5	0.5	0.6
		D_4	-	-	-	-	-	-	-
122	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.8	0.2	0.8	0.2	0.8	0.2	0.2
		D_2	0.4	-	0.4	0.5	0.4	0.5	0.5
		D_3	-	-	-	-	0.9	0.9	0.1
		D_4	-	-	-	-	-	-	-
123	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.1	0.9	0.1	0.9	0.1	0.1	0.9
		D_2	0.9	-	0.9	-	0.9	0.9	-
		D_3	-	-	0.2	-	0.2	0.2	-
		D_4	-	-	-	0.7	-	-	0.7

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
124	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.1	0.9	0.1	0.9	0.1	0.9	0.1
			D_1	0.1	0.1	-	0.1	-	0.1
			D_2	-	0.5	-	0.5	-	0.5
			D_3	-	-	-	0.9	-	0.9
125	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.1	0.9	0.1	0.9	0.1	0.9	0.1
			D_1	0.4	0.4	0.2	0.4	0.2	0.4
			D_2	-	-	-	-	0.1	-
			D_3	-	-	-	-	-	0.1
126	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.2	0.8	0.2	0.8	0.2	0.8	0.2
			D_1	0.4	0.4	-	0.4	-	0.4
			D_2	-	-	0.6	-	0.6	-
			D_3	-	-	-	-	0.9	-
127	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
			D_1	-	0.8	0.8	-	0.8	-
			D_2	-	-	-	-	-	-
			D_3	-	0.3	-	0.3	0.4	0.4
128	6	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
			D_1	-	0.8	0.8	-	0.8	-
			D_2	-	-	-	-	-	-
			D_3	-	0.3	-	0.3	0.4	0.4

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
128	1	Priors	0.7	0.7	0.3	0.7	0.3	0.7	0.3
		D_1	0.6	0.6	-	0.6	-	0.6	-
		D_2	-	0.9	-	0.9	-	0.9	-
		D_3	-	-	-	0.9	-	0.9	-
		D_4	-	-	-	-	-	0.3	-
129	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.3	0.7	0.3	0.7	0.3	0.7	0.7
		D_2	0.4	-	0.4	0.7	0.4	0.7	0.7
		D_3	-	-	-	-	-	-	0.5
		D_4	-	-	-	-	-	-	-
130	4	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_2	0.4	-	0.4	0.2	0.4	0.4	0.2
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
131	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.1	0.9	0.1	0.9	0.1	0.1	0.9
		D_2	-	0.3	-	0.3	-	-	0.3
		D_3	-	-	-	-	-	0.3	-
		D_4	-	-	0.3	-	0.3	0.1	-

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
132	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	-	0.2	-	0.2	-	0.2	-
		D_2	-	-	-	0.5	-	0.5	-
		D_3	-	-	-	-	-	0.8	-
133	4	D_4	-	-	-	-	-	0.1	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.4	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.9	-	0.9	0.4	0.9	0.4	0.9
		D_2	-	-	-	-	0.2	-	0.2
134	1	D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.8	0.2	0.8	0.2	0.8	0.2	0.8
		D_1	0.1	-	0.1	-	0.1	-	0.1
135	1	D_2	-	-	0.9	-	0.9	-	0.9
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.9	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	-	0.4	-	0.4	-	0.4	-
		D_2	-	-	0.2	-	0.2	-	0.2
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
		H_1	H_2	H_1	H_2	H_1	H_2	H_1	H_2
136	1	Priors	0.6	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.5	0.5	-	0.5	-	0.5	-
		D_2	-	0.5	-	0.5	-	0.5	-
		D_3	-	-	-	0.1	-	0.1	0.1
		D_4	-	-	-	-	-	-	-
137	1	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.5	0.5	0.5	0.5	0.5	0.5	0.5
		D_2	-	0.8	0.2	0.8	0.2	0.8	0.2
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
138	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.7	0.3	0.7	0.3	0.7	0.3	0.3
		D_2	-	0.1	0.8	0.1	0.8	0.1	0.1
		D_3	-	-	-	-	-	-	0.2
		D_4	-	-	-	-	0.5	0.5	-
139	2	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_2
		D_1	0.2	0.8	0.2	0.8	0.2	0.2	0.8
		D_2	-	0.3	0.1	0.3	0.1	0.1	0.3
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	0.6	0.6	0.1

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
140	3	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.4	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	0.9	-	0.9	0.5	0.9	0.5	0.9
		D_2	-	-	-	-	-	-	-
		D_3	-	-	-	-	0.1	0.4	0.1
141	4	D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.6	0.4	0.6	0.4	0.6	0.4	0.6
		D_1	0.3	-	0.3	0.2	0.3	0.2	0.3
		D_2	-	-	-	-	-	-	-
142	4	D_3	-	-	-	-	0.8	0.7	0.8
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.4	0.6	0.4	0.6	0.4	0.6	0.4
		D_1	-	0.9	-	0.9	-	0.9	-
143	6	D_2	-	-	-	-	-	-	-
		D_3	-	-	-	0.6	-	0.6	-
		D_4	-	-	-	-	0.4	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.7	0.3	0.7	0.3	0.7	0.3	0.7
144	6	D_1	0.2	-	0.2	0.7	0.2	0.7	0.2
		D_2	-	-	-	-	0.5	-	0.5
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1

Appendix Table D4: (Continued)

Participant	Question	Initial table		First selection		Second Selection		Third selection	
144	5	Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.7	0.3	0.7	0.3	0.7	0.3	0.7
		D_1	-	0.2	-	0.2	-	0.2	-
		D_2	-	-	0.2	-	0.2	-	0.2
		D_3	-	-	-	-	0.9	-	-
145	6	D_4	-	-	-	-	0.4	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.1	0.9	0.1	0.9	0.1	0.9	0.1
		D_1	0.6	-	0.6	0.2	0.6	0.2	0.6
		D_2	-	-	-	-	-	-	-
146	1	D_3	-	-	-	-	0.1	0.1	0.1
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.9	0.1	0.9	0.1	0.9	0.1	0.9
		D_1	0.8	-	0.8	-	0.8	-	0.8
147	6	D_2	-	-	-	-	-	0.5	-
		D_3	-	-	-	-	0.5	-	-
		D_4	-	-	0.1	-	0.1	-	0.1
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1
			0.1	0.9	0.1	0.9	0.1	0.9	0.1
148	6	D_1	-	0.1	0.4	0.1	0.4	0.1	0.4
		D_2	-	-	-	-	0.5	-	-
		D_3	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-
		Priors	H_1	H_2	H_1	H_2	H_1	H_2	H_1

D.3 Experiment 4: Participant selections

D.3.1 First exercise

Appendix Table D5: Participant selections for the three hypotheses, four diagnostic criteria contingency tables: First exercise

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
001	6	Priors			0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3
		D_1	0.5	-	-	0.5	0.6	0.5	-	0.6	0.5	-	0.6	0.5	-	0.6	0.5	-	0.6
		D_2	-	-	-	-	-	-	0.2	-	-	0.2	-	-	0.2	0.6	-	0.2	0.6
		D_3	-	-	-	-	-	-	-	-	0.8	-	-	0.8	-	-	0.8	-	0.8
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
002	3	Priors			0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3
		D_1	-	0.2	-	-	0.2	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-
		D_2	-	-	-	0.3	-	0.3	-	-	0.3	-	-	0.3	-	0.6	0.3	-	0.6
		D_3	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-
		D_4	-	-	-	-	-	-	-	-	-	0.5	-	-	0.5	-	-	0.5	0.8
003	6	Priors			0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1
		D_1	0.7	-	-	0.7	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	-
		D_2	-	-	-	0.7	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	-
		D_3	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	0.1	0.3	-	0.1
		D_4	-	-	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	0.1

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
008	4	Priors	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1
			D_1	-	0.5	-	0.5	0.5	-	0.8	0.5	0.5	0.8	0.5	0.5	0.8	0.5	0.5	0.8
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	0.2	-	-	0.2	-	-	0.2
			D_4	-	-	-	-	-	-	-	-	-	-	-	0.7	-	0.3	0.7	-
009	6	Priors	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2
			D_1	0.9	-	-	0.9	0.8	-	0.7	0.9	0.8	0.7	0.9	0.8	0.7	0.9	0.8	0.7
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_4	-	-	-	-	-	-	-	-	0.9	-	0.3	0.9	-	0.3	0.9	0.2
010	1	Priors	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4
			D_1	-	0.1	-	0.3	0.1	-	-	0.3	0.1	-	0.3	0.1	-	0.3	0.1	-
			D_2	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6
			D_3	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	0.3	-	0.3
			D_4	-	-	-	-	-	-	-	-	-	-	-	0.4	-	-	0.4	-
011	4	Priors	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2
			D_1	0.1	-	-	0.1	0.8	-	0.6	0.1	0.8	0.6	0.1	0.8	0.6	0.1	0.8	0.6
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_4	-	-	-	-	-	-	-	0.8	-	-	0.8	0.6	-	0.8	0.6	0.5

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection				
016	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3				
			D_1	0.8	-	0.8	-	-	0.8	-	-	0.8	0.8	-	0.8	0.8	-	0.8	0.8	-	
			D_2	-	-	-	-	-	0.7	-	-	0.7	-	-	0.9	0.7	-	0.9	0.7	-	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.8	-	-	
D_4	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-			
017	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	
			D_1	0.3	-	0.3	0.6	-	0.3	0.6	0.4	0.3	0.6	0.4	0.3	0.6	0.4	0.3	0.6	0.4	0.4
			D_2	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	0.4	-	-
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
018	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	
			D_1	-	0.9	-	0.3	0.9	-	0.3	0.9	0.6	0.3	0.9	0.6	0.3	0.9	0.6	0.3	0.9	0.6
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	0.9	-	-	0.9	0.7	-	0.9	0.7	0.5
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
019	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	
			D_1	0.6	-	-	0.6	-	-	0.6	-	-	0.6	0.7	-	0.6	0.7	-	0.6	0.7	-
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	0.8	-	-	0.8	-	-
			D_3	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-
D_4	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	0.3		

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
020	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2		
			D_1	0.8	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	-	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	0.9	-	-	0.9	0.1	-	0.9	0.1	0.3	0.9	0.1	0.3	0.3	
		D_4	-	-	-	-	-	-	-	-	-	0.7	-	-	0.7	-	0.3		
021	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2		
			D_1	0.5	-	0.5	0.1	-	0.5	0.1	0.3	0.5	0.1	0.3	0.5	0.1	0.3	0.3	
			D_2	-	-	-	-	-	-	-	-	0.3	-	-	0.3	0.5	-	0.3	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
022	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.3	
			D_1	0.3	-	0.3	0.9	-	0.3	0.9	-	0.3	0.9	-	0.3	0.9	-	0.3	
			D_2	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	
			D_3	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	
		D_4	-	-	-	-	-	-	-	-	-	-	-	0.7	-	-			
023	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.3	
			D_1	-	0.2	-	-	0.2	-	-	0.2	-	0.2	-	-	0.2	-	-	
			D_2	-	-	-	0.6	-	0.6	-	0.2	0.6	-	0.2	0.6	-	0.2	0.2	
			D_3	-	-	-	-	-	-	-	-	-	0.3	-	0.8	0.3	-	-	
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	0.6			

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection			
028	1	H_1 H_2 H_3			H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	
		Priors	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8
		D_1	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	0.2
		D_2	-	-	-	-	-	-	-	-	-	0.3	-	-	-	0.3	-	-	0.3	-
		D_3	-	-	-	-	0.9	-	-	0.8	-	0.9	0.8	-	0.6	0.9	0.8	0.6	0.9	0.8
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
029	4	H_1 H_2 H_3			H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	
		Priors	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2
		D_1	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	0.3
		D_2	-	-	-	-	-	-	-	-	-	0.7	-	-	0.6	0.7	-	0.6	0.7	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	0.1	-	-	-	-	-	0.1
D_4	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-	-		
030	3	H_1 H_2 H_3			H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	
		Priors	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2
		D_1	0.6	-	-	0.6	-	0.6	0.6	0.4	0.6	0.6	0.4	0.6	0.6	0.4	0.6	0.6	0.4	0.6
		D_2	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	0.7
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.6
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
031	4	H_1 H_2 H_3			H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	
		Priors	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2
		D_1	0.2	-	-	0.2	0.1	-	0.2	0.1	0.5	0.2	0.1	0.5	0.2	0.1	0.5	0.2	0.1	0.5
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
D_4	-	-	-	-	-	-	-	-	-	-	-	0.5	-	0.7	0.5	0.5	0.7	0.5		

Appendix Table D5: (Continued)

[illegible]

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
040	3	Priors	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1
			D_1	0.7	-	0.7	0.1	-	0.7	0.1	0.8	0.7	0.1	0.8	0.7	0.1	0.8	0.7	0.1
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	0.7	-	-
			D_4	-	-	-	-	-	-	-	0.5	-	-	0.5	-	0.5	0.5	-	0.5
041	6	Priors	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3
			D_1	0.7	-	0.7	0.3	-	0.7	0.3	0.1	0.7	0.3	0.1	0.7	0.3	0.1	0.7	0.3
			D_2	-	-	-	-	-	-	-	0.8	-	-	0.8	0.5	-	0.8	0.5	0.9
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
042	3	Priors	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1
			D_1	-	0.8	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8
			D_2	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	0.7	-	-
			D_3	-	-	-	-	-	-	-	0.8	0.8	0.5	-	0.8	0.5	0.3	0.8	0.5
			D_4	-	-	-	-	-	-	-	-	-	-	0.9	-	-	0.9	-	-
043	1	Priors	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7
			D_1	0.7	-	0.7	0.3	-	0.7	0.3	-	0.7	0.3	-	0.7	0.3	-	0.7	0.3
			D_2	-	-	-	-	-	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5
			D_3	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-
			D_4	-	-	-	-	-	-	-	-	-	-	-	0.7	-	-	0.7	-

[illegible]

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
052	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4		
			D_1	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5	0.7	
			D_2	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	
			D_3	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-	
		D_4	-	-	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	-		
053	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2		
			D_1	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	
			D_2	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	
			D_3	-	-	-	-	-	-	0.2	-	-	0.2	-	-	0.2	0.6	0.4	
		D_4	-	-	-	-	-	-	-	-	-	-	-	0.9	-	-			
054	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5		
			D_1	-	-	-	0.4	0.2	-	0.4	0.2	0.1	0.4	0.2	0.1	0.4	0.2	0.1	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	-	-	-	-	-	-	-	0.5	-	-	0.5	0.8	0.6	
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
055	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4		
			D_1	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	
			D_2	-	-	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-	0.9	
			D_3	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-	0.8	
		D_4	-	-	-	-	-	-	-	-	-	-	0.6	-	-	0.6			

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
064	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1		
			D_1	0.3	-	0.3	0.2	-	0.3	0.2	0.4	0.3	0.2	0.4	0.3	0.2	0.4		
			D_2	-	-	-	-	-	-	0.8	-	0.8	0.8	-	0.8	0.8	0.6		
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
065	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1		
			D_1	0.2	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-	-		
			D_2	-	-	-	0.5	-	-	0.5	-	-	0.5	-	0.9	0.5	-		
			D_3	-	-	-	-	-	0.8	-	-	-	-	0.8	-	-	0.8		
066	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6		
			D_1	0.3	-	0.3	-	-	0.3	0.3	-	0.3	0.3	-	0.3	0.3	-		
			D_2	-	-	-	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5		
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
067	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1		
			D_1	0.8	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	0.8		
			D_2	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-		
			D_3	-	-	-	-	-	0.2	-	-	0.2	-	-	0.2	-	-		

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
068	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1		
			D_1	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	0.3	
			D_2	-	-	-	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-	
			D_3	-	-	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	
069	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1		
			D_1	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5	-	
			D_2	-	-	-	-	-	-	-	-	0.8	0.7	-	0.8	0.7	-	0.8	
			D_3	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	
070	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1		
			D_1	0.9	-	-	0.9	0.6	0.9	0.9	0.6	0.9	0.9	0.6	0.9	0.9	0.6	0.9	
			D_2	-	-	-	-	-	-	0.3	-	-	0.3	0.4	-	0.3	0.4	0.7	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
071	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1		
			D_1	0.5	-	-	0.5	0.2	0.5	0.5	0.2	0.5	0.5	0.2	0.5	0.5	0.2	0.5	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-	

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
072	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2		
			D_1	0.4	-	-	0.4	-	-	0.4	-	0.2	0.4	-	0.2	0.4	-	0.2	
			D_2	-	-	-	0.8	-	-	0.8	-	-	-	0.8	-	0.5	0.8	0.5	
			D_3	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	
073	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3		
			D_1	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	0.3	-	0.3	-	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	-	0.1	-	0.5	0.1	0.1	0.5	0.1	0.1	0.5	0.1	0.1	0.5	
074	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1		
			D_1	0.1	-	-	0.1	0.3	0.1	0.1	0.3	0.1	0.1	0.3	0.1	0.1	0.3	0.1	
			D_2	-	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-	
			D_3	-	-	-	-	-	-	-	-	-	-	0.2	-	-	0.2	-	
075	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1		
			D_1	0.6	-	-	0.6	0.2	-	0.6	0.2	-	0.6	0.2	-	0.6	0.2	-	
			D_2	-	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-	
			D_3	-	-	-	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
100	1	Priors	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1
		D_1	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-
		D_2	-	-	-	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.6	-	0.4
		D_4	-	-	-	-	-	-	0.4	-	-	0.4	-	-	0.4	-	0.4	-	-
101	1	Priors	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1
		D_1	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	0.9	0.1	-	0.9	0.1
		D_2	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7
		D_3	-	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6
		D_4	-	-	-	-	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1
102	5	Priors	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2
		D_1	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-
		D_2	-	-	-	-	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	-
		D_3	-	-	-	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-
		D_4	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	0.6	-	0.3	0.6
103	3	Priors	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6
		D_1	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	0.9	-	0.9	-
		D_4	-	-	-	0.2	-	-	0.2	0.5	-	0.2	0.5	0.7	0.2	0.5	0.7	0.2	0.5

[illegible]

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection				
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
120	1	Priors	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	
			D_1	0.3	-	-	0.3	0.1	-	0.3	0.1	0.1	0.3	0.1	0.1	0.3	0.1	0.1	0.3	0.1	0.1
			D_2	-	-	-	-	-	-	-	-	-	0.9	-	-	0.9	0.9	-	0.9	0.9	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.3	-
			D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
121	5	Priors	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	
			D_1	0.8	-	-	0.8	0.5	-	0.8	0.5	0.3	0.8	0.5	0.3	0.8	0.5	0.3	0.8	0.5	0.3
			D_2	-	-	-	-	-	-	-	-	-	0.7	-	-	0.7	0.2	-	0.7	0.2	0.6
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
122	5	Priors	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	
			D_1	-	0.2	-	0.4	0.2	-	0.4	0.2	0.7	0.4	0.2	0.7	0.4	0.2	0.7	0.4	0.2	0.7
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.6
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.4	-	-	0.4
			D_4	-	-	-	-	-	-	-	-	-	-	-	0.8	-	-	0.8	-	-	0.8
123	2	Priors	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	
			D_1	0.5	-	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5	0.7	-	0.5	0.7	-
			D_2	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	0.5	-
			D_3	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	-
			D_4	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
124	1	Priors	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1
			D_1	0.1	-	-	0.1	-	0.4	0.1	-	0.4	0.1	-	0.4	0.1	-	0.4	0.1
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.9
			D_4	-	-	-	-	-	-	0.2	-	0.1	0.2	0.5	0.1	0.2	0.5	0.1	0.2
125	6	Priors	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2
			D_1	0.4	-	-	0.4	-	-	0.4	-	-	0.6	0.4	-	0.5	0.4	-	0.5
			D_2	-	-	-	-	0.6	-	-	0.6	-	-	-	0.6	-	-	0.6	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	0.4	-	0.7	0.4
			D_4	-	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-	-
126	3	Priors	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.2	0.4	0.4
			D_1	-	0.7	-	-	0.7	-	-	-	-	0.7	-	-	0.7	-	0.7	-
			D_2	-	-	-	-	-	-	-	-	-	-	-	0.2	-	-	0.4	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_4	-	-	-	0.9	-	-	0.9	0.9	0.9	0.3	0.9	0.9	0.3	0.9	0.9	0.3
127	4	Priors	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4
			D_1	0.5	-	-	0.5	-	-	0.5	-	-	-	0.5	0.5	-	0.5	0.5	0.8
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_4	-	-	-	0.3	-	-	0.3	-	0.3	0.4	0.3	0.3	0.4	0.3	0.4	0.3

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
128	5	Priors	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4
		D_1	0.9	-	-	0.9	-	-	0.9	-	0.9	-	-	0.9	-	0.7	0.9	-	0.7
		D_2	-	-	-	-	0.8	-	-	0.8	-	0.8	-	-	0.8	-	-	0.8	-
		D_3	-	-	-	-	-	-	0.3	-	0.3	-	-	0.3	-	-	0.3	-	-
		D_4	-	-	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-	0.5
129	3	Priors	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1
		D_1	-	0.6	-	0.8	0.6	-	0.8	0.6	0.7	0.8	0.6	0.7	0.8	0.6	0.7	0.8	0.6
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.2	-	0.6
		D_4	-	-	-	-	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-
130	3	Priors	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2
		D_1	0.2	-	-	0.2	0.3	-	0.2	0.3	0.7	0.2	0.3	0.7	0.2	0.3	0.2	0.3	0.7
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.7
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.4
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.2
131	5	Priors	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1
		D_1	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	0.6	-	-
		D_2	-	-	-	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5	0.5	0.5	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	0.5	0.7	-	0.7	-	0.5
		D_4	-	-	-	-	-	-	-	-	0.5	-	-	-	0.5	-	0.5	-	-

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
132	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6		
			D_1	-	0.6	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	
			D_2	-	-	0.2	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-	-
			D_3	-	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-
		D_4	-	-	-	-	-	-	-	0.6	-	0.4	0.6	0.2	0.4	0.6	0.6		
133	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.2	
			D_1	0.2	-	0.2	0.5	-	0.2	0.5	0.4	0.2	0.5	0.4	0.2	0.5	0.4	0.2	0.5
			D_2	-	-	-	-	-	-	-	-	0.4	-	-	0.4	0.3	-	0.4	0.3
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.5	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
134	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	
			D_1	0.8	-	0.8	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	0.8
			D_2	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.6	-
		D_4	-	-	-	-	-	0.1	-	0.4	0.1	-	0.4	0.1	-	0.4	0.4		
135	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	
			D_1	0.6	-	0.6	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-
			D_2	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	-
			D_3	-	-	-	-	-	0.2	-	0.1	0.2	-	0.1	0.2	-	0.1	0.2	0.2
		D_4	-	-	-	-	-	-	-	-	-	-	-	0.9	-	-	-		

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection				
140	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3				
			D_1	0.2	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-	0.2	-	0.5		
			D_2	-	-	-	0.9	-	-	0.9	-	-	-	0.9	-	-	-	0.9	-		
			D_3	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	0.3	-	0.3	
D_4	-	-	-	-	-	-	-	-	-	0.8	-	-	-	-	-	-	0.8				
141	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	
			D_1	-	0.9	-	0.4	0.9	-	0.4	0.9	0.3	0.4	0.9	0.3	0.4	0.9	0.3	0.4	0.9	0.3
			D_2	-	-	-	-	-	-	-	-	-	0.7	-	-	0.7	0.4	-	0.7	0.4	0.9
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
142	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	
			D_1	0.2	-	-	0.2	0.6	-	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2
			D_2	-	-	-	-	-	-	-	-	-	-	0.1	-	-	0.1	-	-	0.1	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	0.6	-	-	0.6	-
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.4	-	-	0.4	-		
143	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3
			D_1	0.8	-	-	0.8	0.7	-	0.8	0.7	0.9	0.8	0.7	0.9	0.8	0.7	0.9	0.8	0.7	0.9
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	0.6	-	-	0.1	0.6	-	0.1	0.6
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
144	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4		
			D_1	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	
			D_2	-	-	-	0.4	-	0.7	0.4	-	0.7	0.4	-	0.7	0.4	-	0.7	
			D_3	-	-	-	-	-	-	-	-	0.3	0.4	-	0.3	0.4	-	0.3	
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.5			
145	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1		
			D_1	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	0.4	0.4	-	
			D_3	-	-	-	-	0.2	0.4	0.6	0.2	0.4	0.6	0.2	0.4	0.6	0.2	0.4	
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
146	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2		
			D_1	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	
			D_2	-	-	-	0.4	-	-	0.4	0.1	-	0.4	0.1	0.2	0.4	0.1	0.2	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	0.8	-	-	
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	0.9	-	-			
147	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3		
			D_1	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.3	0.8	-
			D_2	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	
			D_3	-	-	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	
D_4	-	-	-	-	-	-	-	-	-	0.1	-	-	0.1	0.3	0.1	0.3	-		

Appendix Table D5: (Continued)

Participant	Question	Initial table			First selection			Second selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
148	6	Priors			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1
		D_1	0.1	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	0.1	0.1	0.8	0.1
		D_2	-	-	0.5	-	-	0.5	0.8	-	0.5	0.8	0.3	0.5	0.8	0.3	0.5	0.8	0.3
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
149	6	Priors			0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3
		D_1	0.6	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-
		D_2	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	0.6	0.7
		D_3	-	-	-	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-
		D_4	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	0.9
150	4	Priors			0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3
		D_1	-	0.5	-	0.8	0.5	0.8	0.5	-	0.8	0.5	-	0.8	0.5	-	0.8	0.5	-
		D_2	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	0.5
		D_3	-	-	-	-	-	-	-	-	0.2	-	-	0.2	-	-	0.2	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.1	-	-

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
008	1	Priors	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.6	0.2
		D_1	-	-	0.3	-	0.2	0.3	0.3	0.2	0.3	0.2	0.3	0.3	0.2	0.3	0.3	0.2	0.3
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-	-	0.7	-	-	0.7	0.3	-	0.7	0.3	0.6
009	1	Priors	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5
		D_1	-	-	0.7	0.6	-	0.7	0.6	0.1	0.7	0.6	0.1	0.7	0.6	0.1	0.6	0.1	0.7
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.5
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-	-	0.1	-	-	0.1	-	0.2	0.1	-	0.2
010	3	Priors	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.8	0.1
		D_1	-	-	0.4	-	0.4	0.4	0.9	0.4	0.4	0.9	0.4	0.4	0.9	0.4	0.9	0.4	0.4
		D_2	-	-	-	-	-	-	-	-	0.3	-	-	0.3	0.9	-	0.3	0.9	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
011	2	Priors	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.7	0.2	0.1
		D_1	-	0.9	-	0.5	0.9	-	0.5	0.9	0.9	0.5	0.9	0.9	0.5	0.9	0.5	0.9	0.9
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-	-	0.1	-	-	0.1	0.5	-	0.1	0.5	0.9

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection			
020	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1			
			D_1	-	0.7	0.8	-	0.7	0.8	0.2	0.7	0.8	0.2	0.7	0.8	0.2	0.7			
			D_2	-	-	-	-	-	-	-	-	0.6	-	-	0.6	-	0.7			
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	0.4			
021	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5			
			D_1	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3			
			D_2	-	-	-	-	0.1	-	-	0.1	-	-	0.8	-	0.1	0.8	0.4	0.1	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	0.4	-	-	0.4	
022	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	
			D_1	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	-	
			D_2	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	
			D_3	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-	
023	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.6	
			D_1	-	0.7	0.3	-	0.7	0.3	-	0.7	0.3	-	0.7	0.3	-	0.7	0.3	-	0.7
			D_2	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-
			D_3	-	-	-	-	-	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection			
024	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2			
			D_1	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	
			D_2	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	
			D_3	-	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	
D_4	-	-	-	-	-	-	-	-	0.5	-	-	0.5	-	-	0.5	-	-			
025	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	
			D_1	-	0.4	0.3	-	0.4	0.3	-	0.4	0.3	-	0.4	0.3	-	0.4	0.3	-	0.4
			D_2	-	-	-	-	-	0.5	-	-	0.5	-	-	0.5	-	-	0.5	-	
			D_3	-	-	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	
D_4	-	-	-	-	-	-	-	-	-	-	-	0.6	-	-	0.6	-				
026	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	
			D_1	-	0.1	-	0.4	0.1	-	0.4	0.1	-	0.4	0.1	-	0.4	0.1	-	0.4	0.1
			D_2	-	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	
			D_3	-	-	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	
D_4	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-			
027	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	
			D_1	-	0.1	0.7	-	0.1	0.7	-	0.1	0.7	-	0.1	0.7	-	0.1	0.7	-	0.1
			D_2	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	
			D_3	-	-	-	-	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	
D_4	-	-	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-				

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection			
032	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2			
			D_1	-	0.9	-	-	0.9	-	0.5	0.9	0.3	0.5	0.9	0.3	0.5	0.9	0.3	0.5	0.9
			D_2	-	-	-	0.9	-	-	0.9	-	-	0.9	-	0.7	0.9	-	0.7	0.9	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.8	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
033	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2
			D_1	-	0.5	0.4	-	0.5	0.4	0.3	0.5	0.4	0.3	0.5	0.4	0.3	0.5	0.4	0.3	0.5
			D_2	-	-	-	-	-	-	-	-	-	-	0.2	0.5	-	0.2	0.5	-	0.2
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	0.3	-	-	-		
034	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1
			D_1	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	0.1	0.9	0.8
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	0.9	-	-	0.9	0.8	-	0.9	0.8	0.1	0.9	0.8	0.1	0.9	0.8
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
035	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1
			D_1	-	0.1	0.8	-	0.1	0.8	0.5	0.1	0.8	0.5	0.1	0.8	0.5	0.1	0.8	0.5	0.1
			D_2	-	-	-	-	-	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	0.9	-	-	0.9	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	0.8	-	-	-		

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
044	1	Priors	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.8	0.1
		D_1	-	-	0.6	0.5	-	0.6	0.5	-	0.6	0.5	-	0.6	0.5	-	0.6	0.5	-
		D_2	-	-	-	-	-	0.3	-	0.3	-	0.3	-	0.3	-	0.3	-	0.3	0.7
		D_3	-	-	-	-	-	-	-	-	0.3	-	0.3	-	0.3	-	0.3	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	0.7	-	-	0.7	-
045	1	Priors	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1
		D_1	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	0.3
		D_2	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-
		D_3	-	-	-	-	-	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	0.4	-	-	0.4	-
046	6	Priors	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2
		D_1	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-	0.4
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.2
		D_3	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	0.9
		D_4	-	-	-	-	-	-	-	-	-	0.5	0.7	0.7	0.5	0.7	0.7	0.5	0.7
047	2	Priors	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1
		D_1	-	0.1	-	0.6	0.1	-	0.6	0.1	-	0.6	0.1	-	0.6	0.1	-	0.6	0.1
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4	-	-	-	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
060	2	Priors	D_1	-	0.1	-	0.4	0.1	-	0.4	0.1	0.8	0.1	0.8	0.1	0.1	0.8	0.1	0.1
			D_2	-	-	-	-	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	0.9	-	-	0.9	-
			D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.8
			Priors	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1
061	5	Priors	D_1	-	0.5	-	-	0.5	0.5	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	0.1	-	0.4	0.1	-	0.4	0.1	0.1
			D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			Priors	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.2	0.7	0.1	0.2	0.7	0.1	0.2
062	2	Priors	D_1	-	-	0.8	-	-	0.8	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2
			D_2	-	-	-	0.3	-	-	0.8	-	-	0.8	-	0.1	0.8	-	0.1	0.8
			D_3	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	-
			D_4	-	-	-	-	0.2	-	-	-	0.2	-	-	0.2	-	0.1	0.2	-
			Priors	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.2	0.7	0.1	0.2	0.7	0.1	0.2
063	2	Priors	D_1	-	-	0.6	-	-	0.6	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1
			D_2	-	-	-	0.2	-	-	0.6	-	-	0.6	-	0.9	0.6	-	0.9	0.6
			D_3	-	-	-	-	-	-	-	-	0.2	-	-	0.2	-	-	0.2	-
			D_4	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	-	0.4	0.3
			Priors	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.1	0.6	0.3	0.1	0.6	0.3	0.1

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection			
072	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1			
			D_1	-	-	0.4	-	-	0.4	0.7	-	0.4	0.7	-	0.4	0.7	0.2	0.4		
			D_2	-	-	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	-	-		
			D_3	-	-	-	-	-	-	-	-	-	0.1	-	-	0.1	-	-		
			H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3	0.3	0.4	0.3			
			D_1	-	0.9	-	-	0.9	-	0.2	0.9	-	0.2	0.9	-	0.2	0.9	-		
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	0.3	-	0.7		
			D_3	-	-	-	-	-	-	-	-	-	-	-	0.7	-	-	0.7		
			H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			-	-	-	0.8	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-		
			073	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
						0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1
						D_1	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	-
D_2	-	-				-	-	-	-	-	-	-	-	-	-	-	-	-		
D_3	-	-				-	0.3	-	-	0.3	0.1	-	0.3	0.1	0.2	0.3	0.1	0.2		
074	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1			
			D_1	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-		
			D_2	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-		
			D_3	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	0.3	-		
075	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1			
			D_1	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-		
			D_2	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-		
			D_3	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3	0.3	-		
			H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
			D_1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
088	2	Priors			0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1
		D_1	-	0.8	0.2	-	0.8	0.2	0.4	0.8	0.2	0.4	0.8	0.2	0.4	0.8	0.2	0.4	0.8
		D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.2
		D_3	-	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	0.3
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	0.6	-	-	0.6
089	4	Priors			0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2
		D_1	-	0.6	-	-	0.6	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	0.5
		D_2	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	0.1	-	0.8	0.1	-
		D_3	-	-	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9
		D_4	-	-	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-
090	3	Priors			0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4
		D_1	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	0.3	-	0.1
		D_2	-	-	-	-	0.4	-	0.4	0.4	-	0.4	0.4	-	0.4	0.4	-	0.4	0.4
		D_3	-	-	-	-	-	-	-	-	0.7	-	-	0.7	-	-	0.7	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	-	0.8	-	-	0.8	-	-
091	6	Priors			0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2	0.6	0.2	0.2
		D_1	-	0.7	-	-	0.7	-	0.7	-	-	0.7	-	-	0.7	-	0.1	0.7	-
		D_2	-	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6
		D_3	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-	0.6	-	-
		D_4	-	-	-	-	-	-	-	-	-	-	0.1	-	0.6	0.1	-	0.6	0.1

Appendix Table D6: (Continued)

[illegible]

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection			
096	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3			
			D_1	-	0.6	-	0.2	0.6	0.8	0.2	0.6	0.8	0.2	0.6	0.8	0.2	0.6			
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.4		
			D_3	-	-	-	-	-	-	-	-	0.5	-	-	0.5	-	0.1	0.5	-	0.1
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
097	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1
			D_1	-	0.7	-	0.8	0.7	0.7	0.8	0.7	0.7	0.8	0.7	0.7	0.8	0.7	0.7	0.8	0.7
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	0.4	0.9	-	0.4	0.9	0.2	0.4
		D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
098	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5	0.1	0.4	0.5
			D_1	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	0.5	-	0.4	0.5	-	0.4
			D_2	-	-	-	-	-	-	-	-	-	-	0.3	-	-	0.3	-	-	-
			D_3	-	-	-	-	-	-	-	0.5	-	-	-	0.5	-	-	-	0.5	-
		D_4	-	-	-	0.5	-	-	-	-	0.5	-	-	0.5	-	-	0.5	-	0.1	
099	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3			
			0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4
			D_1	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1
			D_2	-	-	-	-	-	-	-	-	-	0.2	-	-	0.2	-	0.2	0.7	
			D_3	-	-	-	-	-	0.8	-	-	0.8	-	-	0.8	-	-	0.8	-	-
		D_4	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-	0.9	-	0.9	-	0.4	

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
100	4				H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
					0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1
					Priors	-	-	-	-	-	-	-	-	-	-	-	-	-	-
					D_1	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3	-	-	0.3
					D_2	-	-	0.1	-	-	0.1	-	-	0.1	-	-	0.1	0.3	-
101	3				H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
					0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1	0.5	0.4	0.1
					Priors	-	-	-	-	-	-	-	-	-	-	-	-	-	-
					D_1	-	0.8	-	0.1	0.8	0.2	0.1	0.8	0.2	0.1	0.8	0.2	0.1	0.8
					D_2	-	-	-	-	-	-	-	0.3	-	0.1	0.3	0.3	0.1	0.3
102	2				H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
					0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1
					Priors	-	0.3	-	-	0.3	-	0.3	-	-	0.3	-	-	0.3	0.3
					D_1	-	-	0.5	-	-	0.5	-	0.4	0.5	-	0.4	0.5	-	0.4
					D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-
103	1				H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
					0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1
					Priors	-	-	-	-	-	-	-	-	-	-	-	-	-	-
					D_1	-	0.8	0.5	-	0.8	0.5	0.1	0.8	0.5	0.1	0.8	0.5	0.1	0.8
					D_2	-	-	-	-	-	-	-	-	0.9	-	0.7	0.9	-	0.7

[illegible]

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
116	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1		
			D_1	-	0.7	-	0.7	-	-	0.7	-	-	0.7	-	-	0.7	-	-	
			D_2	-	-	-	0.6	-	0.6	-	-	0.6	-	-	0.6	0.5	-	-	
			D_3	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	0.8	-	0.8	
D_4	-	-	-	-	-	-	0.6	-	-	0.6	-	-	0.6	-	-				
117	5	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4	0.2	0.4	0.4		
			D_1	-	-	0.4	0.2	-	0.2	0.9	0.4	0.2	0.9	0.4	0.2	0.9	0.4		
			D_2	-	-	-	-	-	-	-	-	0.4	-	-	0.4	0.6	0.1		
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-					
118	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6		
			D_1	-	0.5	-	-	0.5	-	-	0.5	-	0.5	-	-	0.5	-		
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	0.6	-		
			D_3	-	-	-	-	-	0.5	-	0.5	-	-	0.5	-	-	0.5		
D_4	-	-	-	-	-	-	0.7	0.7	0.7	0.1	-	0.7	0.1	-	0.7				
119	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3		
			D_1	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4	-	-	0.4		
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-		
			D_3	-	-	-	0.7	-	0.7	-	0.9	0.7	0.1	0.9	0.7	0.1	0.9		
D_4	-	-	-	-	-	-	-	-	-	-	-	0.2	-	0.2	0.3				

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection				
120	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7				
			D_1	-	0.6	-	-	0.6	-	-	0.6	0.3	-	0.6	0.3	-	0.6	0.3	-	0.6	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	-	-	0.3	-	0.1	0.3	-	0.1	0.3	-	0.1	0.3	-	0.1	0.3	-
D_4	-	-	-	-	-	-	-	-	-	-	-	-	0.5	-	-	0.5	-	0.8			
121	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	0.1	0.8	0.1	
			D_1	-	0.8	-	0.9	0.8	-	0.9	0.8	0.3	0.9	0.8	0.3	0.9	0.8	0.3	0.9	0.8	0.3
			D_2	-	-	-	-	-	-	-	-	-	0.4	-	-	0.4	0.9	-	0.4	0.9	0.5
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-			
122	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	
			D_1	-	0.6	-	0.1	0.6	0.5	0.1	0.6	0.5	0.1	0.6	0.5	0.1	0.6	0.5	0.1	0.6	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.5	-	0.7	-
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.3			
123	4	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3				
			0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	0.3	0.1	0.6	
			D_1	-	0.7	0.1	-	0.7	0.1	0.3	0.7	0.1	0.3	0.7	0.1	0.3	0.7	0.1	0.3	0.7	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.2
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.1	-	-	-
D_4	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	0.9	-			

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
136	2	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2		
			D_1	-	0.5	-	0.1	0.5	-	0.1	0.5	0.7	0.1	0.5	0.7	0.1	0.5	0.7	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	-	-	-	-	-	-	0.4	-	0.5	0.4	-	0.5	0.4	
137	6	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2		
			D_1	-	0.1	0.5	-	0.1	0.5	-	0.1	0.5	-	0.1	0.5	-	0.1	0.5	
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
138	3	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1	0.7	0.2	0.1		
			D_1	-	-	0.9	0.5	-	0.9	0.5	0.3	0.9	0.5	0.3	0.9	0.5	0.3	0.9	
			D_2	-	-	-	-	-	-	-	-	-	0.6	-	0.3	0.6	0.5	0.3	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
139	1	Priors	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3		
			0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3	0.6	0.1	0.3		
			D_1	-	0.8	-	0.1	0.8	0.9	0.1	0.8	0.9	0.1	0.8	0.9	0.1	0.8		
			D_2	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	
			D_3	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	

[illegible]

Appendix Table D6: (Continued)

Participant	Question	Initial table			First selection			Second Selection			Third selection			Fourth Selection			Fifth selection		
		H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3	H_1	H_2	H_3
148	3	Priors			0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5	0.3	0.2	0.5
		D_1			-	-	0.8	0.9	-	0.8	0.9	0.6	0.8	0.9	0.6	0.8	0.9	0.6	0.8
		D_2			-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3			-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_4			-	-	-	-	-	-	0.2	-	-	0.2	0.1	-	0.2	0.1	0.9
149	1	Priors			0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7	0.1	0.2	0.7
		D_1			-	-	0.2	-	-	0.2	-	-	0.2	-	-	0.2	0.5	-	0.2
		D_2			-	-	-	-	0.1	-	-	0.1	-	0.6	0.1	-	0.6	0.1	-
		D_3			-	-	-	-	-	-	0.4	-	-	0.4	-	-	0.4	-	-
		D_4			-	-	-	-	-	-	0.9	-	-	0.9	-	-	0.9	-	-
150	1	Priors			0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3	0.5	0.2	0.3
		D_1			-	-	0.2	-	-	0.2	0.1	-	0.2	0.1	0.4	0.2	0.1	0.4	0.2
		D_2			-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
		D_3			-	-	-	-	-	-	-	-	-	-	-	-	-	0.6	-
		D_4			-	-	-	-	0.1	-	0.2	0.1	-	0.2	0.1	-	0.2	0.1	-

Appendix E

Experiment 5: Participant estimations of probability

E.1 Participant estimations of $P(H_1|D_1, D_2)$ for a 2×2 contingency table

Appendix Table E1: Participant estimations of $P(H_1|D_1, D_2)$ for the two hypotheses, two diagnostic criteria contingency tables

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
001	0.50	0.1563	0.1747	0.3438	0.3253
002	0.40	0.3488	0.3619	0.0512	0.0381

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
003	0.40	0.1037	0.0992	0.2963	0.3008
004	0.70	0.6269	0.6400	0.0731	0.0600
005	0.60	0.7368	0.7454	-0.1368	-0.1454
006	0.25	0.2059	0.1376	0.0441	0.1124
007	0.35	0.2727	0.2285	0.0773	0.1215
008	0.50	0.1000	0.1000	0.4000	0.4000
009	0.80	0.8000	0.8000	0.0000	0.0000
010	0.20	0.4375	0.4241	-0.2375	-0.2241
011	0.50	0.3333	0.2787	0.1667	0.2213
012	0.40	0.0716	0.0643	0.3284	0.3357

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
013	0.70	0.1091	0.0825	0.5909	0.6175
014	0.40	0.5283	0.4859	-0.1283	-0.0859
015	0.95	0.9351	0.9414	0.0149	0.0086
016	0.85	0.8649	0.8771	-0.0149	-0.0271
017	0.20	0.1463	0.1187	0.0537	0.0813
018	0.10	0.3913	0.4190	-0.2913	-0.3190
019	0.60	0.8663	0.8727	-0.2663	-0.2727
020	0.50	0.8182	0.8593	-0.3182	-0.3593
021	0.80	0.9412	0.9571	-0.1412	-0.1571
022	0.20	0.8000	0.8000	-0.6000	-0.6000

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
023	0.45	0.1825	0.1757	0.2675	0.2743
024	0.70	0.8276	0.8338	-0.1276	-0.1338
025	0.40	0.0422	0.0363	0.3578	0.3637
026	0.50	0.4000	0.4000	0.1000	0.1000
027	0.15	0.0769	0.0724	0.0731	0.0776
028	0.70	0.9474	0.9555	-0.2474	-0.2555
029	0.20	0.4375	0.4241	-0.2375	-0.2241
030	0.50	0.8333	0.8824	-0.3333	-0.3824
031	0.55	0.6000	0.6000	-0.0500	-0.0500
032	0.30	0.3333	0.3708	-0.0333	-0.0708

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
033	0.25	0.4000	0.3286	-0.1500	-0.0786
034	0.20	0.0968	0.0692	0.1032	0.1308
035	0.65	0.8663	0.8592	-0.2163	-0.2092
036	0.25	0.4098	0.3979	-0.1598	-0.1479
037	0.15	0.2577	0.2273	-0.1077	-0.0773
038	0.45	0.4000	0.4000	0.0500	0.0500
039	0.00	0.8182	0.7925	-0.8182	-0.7925
040	0.50	0.9153	0.9186	-0.4153	-0.4186
041	0.80	0.9333	0.9502	-0.1333	-0.1502
042	0.35	0.3333	0.2895	0.0167	0.0605

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
043	0.60	0.4286	0.4980	0.1714	0.1020
044	0.20	0.8000	0.7683	-0.6000	-0.5683
045	0.50	0.6000	0.6000	-0.1000	-0.1000
046	0.40	0.5676	0.5603	-0.1676	-0.1603
047	0.80	0.5989	0.5989	0.2011	0.2011
048	0.30	0.3077	0.3904	-0.0077	-0.0904
049	0.55	0.7576	0.7717	-0.2076	-0.2217
050	0.60	0.9231	0.9284	-0.3231	-0.3284
051	0.60	0.6087	0.5810	-0.0087	0.0190
052	0.60	0.8366	0.8478	-0.2366	-0.2478

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
053	0.50	0.5714	0.6207	-0.0714	-0.1207
054	0.90	0.3103	0.3396	0.5897	0.5604
055	0.50	0.5000	0.5000	0.0000	0.0000
056	0.50	0.7000	0.7000	-0.2000	-0.2000
057	0.50	0.9000	0.9000	-0.4000	-0.4000
058	0.25	0.0667	0.0498	0.1833	0.2002
059	0.10	0.3226	0.3053	-0.2226	-0.2053
060	0.85	0.5102	0.5788	0.3398	0.2712
061	0.15	0.1385	0.1126	0.0115	0.0374
062	0.50	0.1250	0.0994	0.3750	0.4006

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
063	0.00	0.0455	0.0285	-0.0455	-0.0285
064	0.65	0.5714	0.6139	0.0786	0.0361
065	0.50	0.3750	0.3204	0.1250	0.1796
066	0.70	0.8065	0.8166	-0.1065	-0.1166
067	0.70	0.0968	0.0800	0.6032	0.6200
068	0.35	0.7407	0.7251	-0.3907	-0.3751
069	0.50	0.6000	0.6000	-0.1000	-0.1000
070	0.60	0.1667	0.1860	0.4333	0.4140
071	0.05	0.3000	0.2580	-0.2500	-0.2080
072	0.25	0.3333	0.2787	-0.0833	-0.0287

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
073	0.75	0.7313	0.7383	0.0187	0.0117
074	0.60	0.2174	0.2612	0.3826	0.3388
075	0.55	0.6000	0.6000	-0.0500	-0.0500
076	0.25	0.4000	0.3286	-0.1500	-0.0786
077	0.40	0.7059	0.6774	-0.3059	-0.2774
078	0.55	0.4444	0.4554	0.1056	0.0946
079	0.90	0.9574	0.9663	-0.0574	-0.0663
080	0.80	0.9524	0.9677	-0.1524	-0.1677
081	0.30	0.8182	0.7905	-0.5182	-0.4905
082	0.80	0.8963	0.9091	-0.0963	-0.1091

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
083	0.50	0.7000	0.7000	-0.2000	-0.2000
084	0.90	0.6494	0.7240	0.2506	0.1760
085	0.50	0.0345	0.0221	0.4655	0.4779
086	0.90	0.8963	0.8963	0.0037	0.0037
087	0.40	0.2809	0.2505	0.1191	0.1495
088	0.60	0.7568	0.7707	-0.1568	-0.1707
089	0.30	0.4286	0.4097	-0.1286	-0.1097
090	0.60	0.9643	0.9728	-0.3643	-0.3728
091	0.80	0.7500	0.7864	0.0500	0.0136
092	0.60	0.2727	0.2065	0.3273	0.3935

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
093	0.30	0.7200	0.6537	-0.4200	-0.3537
094	0.40	0.8000	0.8000	-0.4000	-0.4000
095	0.75	0.7778	0.7948	-0.0278	-0.0448
096	0.40	0.0769	0.0579	0.3231	0.3421
097	0.80	0.9657	0.9758	-0.1657	-0.1758
098	0.20	0.2727	0.2119	-0.0727	-0.0119
099	0.15	0.1429	0.1293	0.0071	0.0207
100	0.60	0.8182	0.7925	-0.2182	-0.1925
101	0.10	0.3636	0.2660	-0.2636	-0.1660
102	0.50	0.4000	0.4000	0.1000	0.1000

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
103	0.80	0.3542	0.3737	0.4458	0.4263
104	0.30	0.1429	0.1557	0.1571	0.1443
105	0.50	0.2000	0.2000	0.3000	0.3000
106	0.60	0.7297	0.7552	-0.1297	-0.1552
107	0.40	0.6184	0.5907	-0.2184	-0.1907
108	0.20	0.7143	0.7407	-0.5143	-0.5407
109	0.40	0.4667	0.4593	-0.0667	-0.0593
110	0.65	0.8571	0.8691	-0.2071	-0.2191
111	0.10	0.1000	0.1000	0.0000	0.0000
112	0.35	0.2553	0.2446	0.0947	0.1054

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
113	0.35	0.3571	0.3470	-0.0071	0.0030
114	0.70	0.1667	0.1589	0.5333	0.5411
115	0.70	0.6923	0.7112	0.0077	-0.0112
116	0.30	0.3165	0.2856	-0.0165	0.0144
117	0.80	0.5161	0.5433	0.2839	0.2567
118	0.85	0.8235	0.8514	0.0265	-0.0014
119	0.30	0.6154	0.5570	-0.3154	-0.2570
120	0.70	0.2718	0.2589	0.4282	0.4411
121	0.75	0.4068	0.4334	0.3432	0.3166
122	0.60	0.5714	0.5075	0.0286	0.0925

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
123	0.10	0.5283	0.4920	-0.4283	-0.3920
124	0.15	0.4375	0.3754	-0.2875	-0.2254
125	0.50	0.3103	0.3396	0.1897	0.1604
126	0.40	0.1453	0.1269	0.2547	0.2731
127	0.20	0.1923	0.1724	0.0077	0.0276
128	0.50	0.7159	0.6801	-0.2159	-0.1801
129	0.45	0.2727	0.2961	0.1773	0.1539
130	0.40	0.9259	0.9312	-0.5259	-0.5312
131	0.20	0.1290	0.1380	0.0710	0.0620
132	0.60	0.2344	0.2203	0.3656	0.3797

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
133	0.95	0.9380	0.9439	0.0120	0.0061
134	0.30	0.2294	0.2095	0.0706	0.0905
135	0.30	0.6923	0.6096	-0.3923	-0.3096
136	0.40	0.3000	0.3000	0.1000	0.1000
137	0.30	0.0506	0.0408	0.2494	0.2592
138	0.55	0.9000	0.9328	-0.3500	-0.3828
139	0.50	0.5714	0.6207	-0.0714	-0.1207
140	0.15	0.1429	0.0930	0.0071	0.0570
141	0.40	0.5091	0.4622	-0.1091	-0.0622
142	0.75	0.7706	0.7950	-0.0206	-0.0450

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
143	0.45	0.3478	0.3350	0.1022	0.1150
144	0.20	0.1463	0.1187	0.0537	0.0813
145	0.40	0.0899	0.0879	0.3101	0.3121
146	0.50	0.0826	0.0826	0.4174	0.4174
147	0.25	0.1429	0.0930	0.1071	0.1570
148	0.60	0.6667	0.7105	-0.0667	-0.1105
149	0.75	0.7500	0.8255	0.0000	-0.0755
150	0.50	0.0847	0.0814	0.4153	0.4186
151	0.70	0.9545	0.9628	-0.2545	-0.2628
152	0.30	0.0426	0.0337	0.2574	0.2663

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
153	0.50	0.9000	0.9000	-0.4000	-0.4000
154	0.20	0.4000	0.3786	-0.2000	-0.1786
155	0.60	0.5556	0.5696	0.0444	0.0304
156	0.40	0.5294	0.5101	-0.1294	-0.1101
157	0.40	0.3243	0.2934	0.0757	0.1066
158	0.20	0.0526	0.0376	0.1474	0.1624
159	0.70	0.6923	0.7163	0.0077	-0.0163
160	0.40	0.2222	0.2070	0.1778	0.1930
161	0.65	0.6897	0.6604	-0.0397	-0.0104
162	0.25	0.3636	0.3818	-0.1136	-0.1318

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
163	0.10	0.1168	0.1168	-0.0168	-0.0168
164	0.50	0.4667	0.4087	0.0333	0.0913
165	0.60	0.9730	0.9811	-0.3730	-0.3811
166	0.50	0.5000	0.3810	0.0000	0.1190
167	0.60	0.0217	0.0146	0.5783	0.5854
168	0.50	0.8421	0.8953	-0.3421	-0.3953
169	0.50	0.5000	0.5000	0.0000	0.0000
170	0.40	0.5556	0.5446	-0.1556	-0.1446
171	0.70	0.3571	0.4545	0.3429	0.2455
172	0.80	0.5714	0.5874	0.2286	0.2126

Appendix Table E1: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, D_2)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, D_2)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, D_2)$	Difference $(A) - (B)$	Difference $(A) - (C)$
173	0.30	0.5172	0.4972	-0.2172	-0.1972
174	0.30	0.3077	0.2692	-0.0077	0.0308
175	0.65	0.1000	0.1000	0.5500	0.5500

E.2 Participant estimations of $P(H_1|D_1, \dots, D_4)$ for a 2×4 contingency table

Appendix Table E2: Participant estimations of $P(H_1|D_1, \dots, D_4)$ for the two hypotheses, four diagnostic criteria contingency tables

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
001	0.50	0.2857	0.2439	0.2143	0.2561
002	0.80	0.7362	0.7581	0.0638	0.0419
003	0.40	0.8182	0.8026	-0.4182	-0.4026
004	0.75	0.5714	0.6031	0.1786	0.1469
005	0.75	0.6667	0.6926	0.0833	0.0574
006	0.70	0.3600	0.3768	0.3400	0.3232
007	0.25	0.0489	0.0424	0.2011	0.2076

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
008	0.10	0.1935	0.1636	-0.0935	-0.0636
009	0.65	0.8033	0.8103	-0.1533	-0.1603
010	0.75	0.1127	0.1146	0.6373	0.6354
011	0.70	0.9423	0.9509	-0.2423	-0.2509
012	0.65	0.8710	0.8891	-0.2210	-0.2391
013	0.60	0.5102	0.5236	0.0898	0.0764
014	0.60	0.0370	0.0279	0.5630	0.5721
015	0.70	0.5385	0.5531	0.1615	0.1469
016	0.60	0.2703	0.2927	0.3297	0.3073
017	0.60	0.2119	0.2177	0.3881	0.3823

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
018	0.90	0.6897	0.7129	0.2103	0.1871
019	0.80	0.8889	0.8984	-0.0889	-0.0984
020	0.65	0.2915	0.2924	0.3585	0.3576
021	0.50	0.4000	0.4593	0.1000	0.0407
022	0.30	0.1409	0.1304	0.1591	0.1696
023	0.15	0.0725	0.0582	0.0775	0.0918
024	0.30	0.7127	0.7341	-0.4127	-0.4341
025	0.55	0.5294	0.5326	0.0206	0.0174
026	0.60	0.7576	0.7900	-0.1576	-0.1900
027	0.30	0.1304	0.1029	0.1696	0.1971

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
028	0.55	0.6000	0.6121	-0.0500	-0.0621
029	0.50	0.4444	0.4377	0.0556	0.0623
030	0.70	0.3333	0.3612	0.3667	0.3388
031	0.75	0.9690	0.9751	-0.2190	-0.2251
032	0.50	0.8421	0.8527	-0.3421	-0.3527
033	0.30	0.2105	0.1695	0.0895	0.1305
034	0.60	0.8000	0.8120	-0.2000	-0.2120
035	0.85	0.7273	0.7137	0.1227	0.1363
036	0.40	0.4167	0.4342	-0.0167	-0.0342
037	0.60	0.6667	0.6821	-0.0667	-0.0821

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
038	0.05	0.0526	0.0402	-0.0026	0.0098
039	0.00	0.0473	0.0391	-0.0473	-0.0391
040	0.70	0.9790	0.9850	-0.2790	-0.2850
041	0.30	0.7297	0.6981	-0.4297	-0.3981
042	0.25	0.0841	0.0704	0.1659	0.1796
043	0.70	0.5161	0.5285	0.1839	0.1715
044	0.10	0.3027	0.3124	-0.2027	-0.2124
045	0.40	0.3000	0.2950	0.1000	0.1050
046	0.60	0.8750	0.8720	-0.2750	-0.2720
047	0.35	0.1923	0.1799	0.1577	0.1701

Appendix Table E2: (Continued)

Participant	(A) estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
048	0.45	0.4737	0.4573	-0.0237	-0.0073
049	0.70	0.2045	0.2062	0.4955	0.4938
050	0.35	0.3797	0.3861	-0.0297	-0.0361
051	0.40	0.1724	0.1695	0.2276	0.2305
052	0.90	0.9730	0.9772	-0.0730	-0.0772
053	0.30	0.7785	0.7587	-0.4785	-0.4587
054	0.30	0.1837	0.1578	0.1163	0.1422
055	0.20	0.1220	0.1242	0.0780	0.0758
056	0.65	0.2308	0.2229	0.4192	0.4271
057	0.95	0.9664	0.9714	-0.0164	-0.0214

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
058	0.70	0.9701	0.9741	-0.2701	-0.2741
059	0.80	0.8861	0.9014	-0.0861	-0.1014
060	0.70	0.8427	0.8780	-0.1427	-0.1780
061	0.25	0.9084	0.9117	-0.6584	-0.6617
062	0.50	0.7874	0.7907	-0.2874	-0.2907
063	0.20	0.3378	0.3246	-0.1378	-0.1246
064	0.40	0.1776	0.1494	0.2224	0.2506
065	0.40	0.7042	0.6923	-0.3042	-0.2923
066	0.30	0.7500	0.7461	-0.4500	-0.4461
067	0.50	0.4275	0.4313	0.0725	0.0687

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
068	0.20	0.2174	0.2331	-0.0174	-0.0331
069	0.60	0.5000	0.5206	0.1000	0.0794
070	0.30	0.4808	0.4352	-0.1808	-0.1352
071	0.25	0.1880	0.1687	0.0620	0.0813
072	0.30	0.5172	0.5088	-0.2172	-0.2088
073	0.75	0.6914	0.7167	0.0586	0.0333
074	0.70	0.9036	0.9075	-0.2036	-0.2075
075	0.70	0.8400	0.8495	-0.1400	-0.1495
076	0.60	0.6667	0.6719	-0.0667	-0.0719
077	0.50	0.8322	0.8615	-0.3322	-0.3615

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
078	0.90	0.9853	0.9934	-0.0853	-0.0934
079	0.30	0.0308	0.0266	0.2692	0.2734
080	0.35	0.1250	0.1145	0.2250	0.2355
081	0.60	0.6973	0.7151	-0.0973	-0.1151
082	0.40	0.6364	0.6466	-0.2364	-0.2466
083	0.40	0.5385	0.4928	-0.1385	-0.0928
084	0.75	0.3333	0.3482	0.4167	0.4018
085	0.30	0.5294	0.5223	-0.2294	-0.2223
086	0.40	0.7297	0.6997	-0.3297	-0.2997
087	0.30	0.4217	0.3934	-0.1217	-0.0934

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
088	0.50	0.2059	0.2260	0.2941	0.2740
089	0.30	0.8537	0.8632	-0.5537	-0.5632
090	0.30	0.8696	0.8747	-0.5696	-0.5747
091	0.40	0.4355	0.4252	-0.0355	-0.0252
092	0.40	0.7742	0.7521	-0.3742	-0.3521
093	0.60	0.4000	0.4548	0.2000	0.1452
094	0.40	0.5625	0.5606	-0.1625	-0.1606
095	0.35	0.4000	0.3756	-0.0500	-0.0256
096	0.75	0.9375	0.9459	-0.1875	-0.1959
097	0.90	0.1000	0.0940	0.8000	0.8060

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
098	0.30	0.5902	0.5825	-0.2902	-0.2825
099	0.80	0.8963	0.9055	-0.0963	-0.1055
100	0.90	0.7941	0.8329	0.1059	0.0671
101	0.50	0.9767	0.9822	-0.4767	-0.4822
102	0.50	0.3846	0.4073	0.1154	0.0927
103	0.80	0.6667	0.6824	0.1333	0.1176
104	0.30	0.6957	0.7385	-0.3957	-0.4385
105	0.75	0.8333	0.8775	-0.0833	-0.1275
106	0.65	0.1818	0.2060	0.4682	0.4440
107	0.75	0.6429	0.6892	0.1071	0.0608

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
108	0.40	0.2727	0.2493	0.1273	0.1507
109	0.40	0.6522	0.6472	-0.2522	-0.2472
110	0.30	0.0625	0.0575	0.2375	0.2425
111	0.75	0.5676	0.5285	0.1824	0.2215
112	0.20	0.7423	0.7270	-0.5423	-0.5270
113	0.70	0.7692	0.7885	-0.0692	-0.0885
114	0.35	0.0886	0.0843	0.2614	0.2657
115	0.20	0.1980	0.1786	0.0020	0.0214
116	0.25	0.0311	0.0238	0.2189	0.2262
117	0.60	0.9643	0.9697	-0.3643	-0.3697

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
118	0.25	0.5932	0.5801	-0.3432	-0.3301
119	0.60	0.8438	0.8382	-0.2438	-0.2382
120	0.40	0.6809	0.6736	-0.2809	-0.2736
121	0.65	0.9231	0.9327	-0.2731	-0.2827
122	0.90	0.9000	0.9000	0.0000	0.0000
123	0.90	0.9120	0.9160	-0.0120	-0.0160
124	0.30	0.0223	0.0189	0.2777	0.2811
125	0.30	0.3425	0.3171	-0.0425	-0.0171
126	0.40	0.1649	0.1474	0.2351	0.2526
127	0.30	0.3571	0.3893	-0.0571	-0.0893

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
128	0.45	0.2174	0.2099	0.2326	0.2401
129	0.50	0.4615	0.4846	0.0385	0.0154
130	0.40	0.1552	0.1445	0.2448	0.2555
131	0.55	0.6183	0.6230	-0.0683	-0.0730
132	0.80	0.2222	0.2255	0.5778	0.5745
133	0.30	0.0385	0.0363	0.2615	0.2637
134	0.10	0.8571	0.8463	-0.7571	-0.7463
135	0.60	0.3750	0.3957	0.2250	0.2043
136	0.25	0.3182	0.3009	-0.0682	-0.0509
137	0.80	0.6154	0.6384	0.1846	0.1616

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
138	0.40	0.0308	0.0271	0.3692	0.3729
139	0.75	0.7344	0.7548	0.0156	-0.0048
140	0.80	0.8750	0.8804	-0.0750	-0.0804
141	0.80	0.9643	0.9672	-0.1643	-0.1672
142	0.60	0.8182	0.8372	-0.2182	-0.2372
143	0.40	0.3590	0.3447	0.0410	0.0553
144	0.00	0.0352	0.0281	-0.0352	-0.0281
145	0.65	0.7273	0.7640	-0.0773	-0.1140
146	0.60	0.4167	0.4301	0.1833	0.1699
147	0.50	0.1429	0.1395	0.3571	0.3605

Appendix Table E2: (Continued)

Participant	(A) estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference (A) – (B)	Difference (A) – (C)
148	0.35	0.7059	0.6963	-0.3559	-0.3463
149	0.35	0.2967	0.2783	0.0533	0.0717
150	0.30	0.6371	0.6663	-0.3371	-0.3663
151	0.70	0.8175	0.8235	-0.1175	-0.1235
152	0.35	0.3333	0.3009	0.0167	0.0491
153	0.50	0.7000	0.7015	-0.2000	-0.2015
154	0.50	0.6000	0.6000	-0.1000	-0.1000
155	0.75	0.6604	0.6828	0.0896	0.0672
156	0.85	0.7706	0.7819	0.0794	0.0681
157	0.50	0.2800	0.3165	0.2200	0.1835

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
158	0.90	0.8448	0.8581	0.0552	0.0419
159	0.20	0.0146	0.0114	0.1854	0.1886
160	0.10	0.0132	0.0097	0.0868	0.0903
161	0.65	0.8389	0.8396	-0.1889	-0.1896
162	0.40	0.0437	0.0402	0.3563	0.3598
163	0.20	0.0162	0.0133	0.1838	0.1867
164	0.40	0.7500	0.7622	-0.3500	-0.3622
165	0.55	0.4118	0.4145	0.1382	0.1355
166	0.25	0.0526	0.0379	0.1974	0.2121
167	0.65	0.3636	0.3815	0.2864	0.2685

Appendix Table E2: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
168	0.75	0.3836	0.3818	0.3664	0.3682
169	0.60	0.8824	0.9012	-0.2824	-0.3012
170	0.30	0.5294	0.5048	-0.2294	-0.2048
171	0.90	0.9492	0.9592	-0.0492	-0.0592
172	0.30	0.8045	0.7897	-0.5045	-0.4897
173	0.85	0.9697	0.9732	-0.1197	-0.1232
174	0.70	0.7200	0.7313	-0.0200	-0.0313
175	0.70	0.6540	0.6823	0.0460	0.0177

E.3 Participant estimations of $P(H_1|D_1, \dots, D_4)$ for a 3×4 contingency table

Appendix Table E3: Participant estimations of $P(H_1|D_1, \dots, D_4)$ for the three hypotheses, four diagnostic criteria contingency tables

Participant	(A)	(B)	(C)	Difference (A) − (B)	Difference (A) − (C)
	Participant estimate of $P(H_1 D_1, \dots, D_4)$	Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$		
001	1.00	0.7073	0.6992	0.2927	0.3008
002	0.60	0.6250	0.6277	-0.0250	-0.0277
003	0.40	0.6231	0.6520	-0.2231	-0.2520
004	0.20	0.0971	0.0908	0.1029	0.1092
005	0.15	0.6840	0.6706	-0.5340	-0.5206
006	0.60	0.5293	0.5541	0.0707	0.0459
007	0.15	0.0333	0.0299	0.1167	0.1201

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
008	0.10	0.0834	0.0818	0.0166	0.0182
009	0.20	0.0540	0.0457	0.1460	0.1543
010	0.10	0.0515	0.0480	0.0485	0.0520
011	0.35	0.2648	0.2615	0.0852	0.0885
012	0.30	0.1772	0.1763	0.1228	0.1237
013	0.20	0.1381	0.1161	0.0619	0.0839
014	0.20	0.1556	0.1346	0.0444	0.0654
015	0.20	0.4507	0.4142	-0.2507	-0.2142
016	0.80	0.3045	0.3404	0.4955	0.4596
017	0.10	0.4425	0.4029	-0.3425	-0.3029

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
018	0.05	0.0858	0.0864	-0.0358	-0.0364
019	0.45	0.1015	0.1028	0.3485	0.3472
020	0.45	0.2857	0.3020	0.1643	0.1480
021	0.10	0.0768	0.0753	0.0232	0.0247
022	0.35	0.8165	0.8445	-0.4665	-0.4945
023	0.10	0.1628	0.1349	-0.0628	-0.0349
024	0.25	0.0808	0.0725	0.1692	0.1775
025	0.65	0.1732	0.1789	0.4768	0.4711
026	0.50	0.6329	0.6242	-0.1329	-0.1242
027	0.95	0.9116	0.9267	0.0384	0.0233

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference (A) – (B)	Difference (A) – (C)
028	0.20	0.4152	0.3808	-0.2152	-0.1808
029	0.70	0.8175	0.8202	-0.1175	-0.1202
030	0.50	0.6649	0.6710	-0.1649	-0.1710
031	0.20	0.6393	0.6546	-0.4393	-0.4546
032	0.40	0.8989	0.9071	-0.4989	-0.5071
033	0.25	0.1316	0.1232	0.1184	0.1268
034	0.40	0.4565	0.4405	-0.0565	-0.0405
035	0.70	0.4345	0.4487	0.2655	0.2513
036	0.20	0.2669	0.2621	-0.0669	-0.0621
037	0.20	0.0760	0.0648	0.1240	0.1352

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
038	0.25	0.1064	0.1008	0.1436	0.1492
039	0.30	0.2500	0.2117	0.0500	0.0883
040	0.60	0.5323	0.5589	0.0677	0.0411
041	0.85	0.9380	0.9445	-0.0880	-0.0945
042	0.20	0.4107	0.4064	-0.2107	-0.2064
043	0.05	0.1699	0.1391	-0.1199	-0.0891
044	0.20	0.2941	0.2679	-0.0941	-0.0679
045	0.60	0.7027	0.7370	-0.1027	-0.1370
046	0.75	0.8306	0.8417	-0.0806	-0.0917
047	0.30	0.4685	0.4158	-0.1685	-0.1158

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
048	0.30	0.0607	0.0577	0.2393	0.2423
049	0.35	0.7478	0.7707	-0.3978	-0.4207
050	0.50	0.2651	0.2734	0.2349	0.2266
051	0.15	0.1144	0.0891	0.0356	0.0609
052	0.65	0.4818	0.4824	0.1682	0.1676
053	0.50	0.8963	0.9085	-0.3963	-0.4085
054	0.50	0.1667	0.1627	0.3333	0.3373
055	0.55	0.7763	0.7831	-0.2263	-0.2331
056	0.40	0.0753	0.0647	0.3247	0.3353
057	0.20	0.1037	0.0963	0.0963	0.1037

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
058	0.30	0.0555	0.0556	0.2445	0.2444
059	0.30	0.6400	0.6682	-0.3400	-0.3682
060	0.70	0.6711	0.6722	0.0289	0.0278
061	0.40	0.6538	0.6849	-0.2538	-0.2849
062	0.20	0.6170	0.5977	-0.4170	-0.3977
063	0.30	0.3157	0.3102	-0.0157	-0.0102
064	0.20	0.5643	0.5506	-0.3643	-0.3506
065	0.50	0.5021	0.4928	-0.0021	0.0072
066	0.20	0.7576	0.7529	-0.5576	-0.5529
067	0.50	0.7571	0.7691	-0.2571	-0.2691

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
068	0.20	0.1130	0.1141	0.0870	0.0859
069	0.10	0.1077	0.1009	-0.0077	-0.0009
070	0.20	0.2848	0.2813	-0.0848	-0.0813
071	0.15	0.0728	0.0703	0.0772	0.0797
072	0.05	0.1217	0.0796	-0.0717	-0.0296
073	0.25	0.1468	0.1530	0.1032	0.0970
074	0.50	0.2496	0.2685	0.2504	0.2315
075	0.80	0.9380	0.9464	-0.1380	-0.1464
076	0.30	0.5128	0.5013	-0.2128	-0.2013
077	0.50	0.7673	0.7944	-0.2673	-0.2944

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
078	0.50	0.2340	0.2089	0.2660	0.2911
079	0.60	0.7865	0.8256	-0.1865	-0.2256
080	0.65	0.7059	0.7157	-0.0559	-0.0657
081	0.60	0.4726	0.4277	0.1274	0.1723
082	0.45	0.5378	0.5595	-0.0878	-0.1095
083	0.25	0.0260	0.0223	0.2240	0.2277
084	0.25	0.1385	0.1431	0.1115	0.1069
085	0.50	0.8524	0.8640	-0.3524	-0.3640
086	0.55	0.8242	0.8254	-0.2742	-0.2754
087	0.10	0.0388	0.0314	0.0612	0.0686

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
088	0.15	0.4325	0.4479	-0.2825	-0.2979
089	0.10	0.5758	0.5637	-0.4758	-0.4637
090	0.25	0.1189	0.1217	0.1311	0.1283
091	0.20	0.1213	0.0960	0.0787	0.1040
092	0.30	0.6410	0.6588	-0.3410	-0.3588
093	0.60	0.7826	0.8099	-0.1826	-0.2099
094	0.60	0.5059	0.5414	0.0941	0.0586
095	0.30	0.7477	0.7407	-0.4477	-0.4407
096	0.65	0.3536	0.3499	0.2964	0.3001
097	0.40	0.7805	0.7774	-0.3805	-0.3774

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
098	0.45	0.5696	0.6030	-0.1196	-0.1530
099	0.25	0.3018	0.3043	-0.0518	-0.0543
100	0.35	0.4091	0.3886	-0.0591	-0.0386
101	0.25	0.4468	0.4203	-0.1968	-0.1703
102	0.10	0.1307	0.1247	-0.0307	-0.0247
103	0.25	0.0977	0.0916	0.1523	0.1584
104	0.35	0.3836	0.4115	-0.0336	-0.0615
105	0.65	0.2783	0.2878	0.3717	0.3622
106	0.50	0.5341	0.5372	-0.0341	-0.0372
107	0.60	0.8301	0.8466	-0.2301	-0.2466

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
108	0.50	0.8995	0.9145	-0.3995	-0.4145
109	0.50	0.3770	0.3499	0.1230	0.1501
110	0.20	0.2680	0.2368	-0.0680	-0.0368
111	0.40	0.9505	0.9677	-0.5505	-0.5677
112	0.10	0.1339	0.1257	-0.0339	-0.0257
113	0.80	0.6769	0.6831	0.1231	0.1169
114	0.40	0.8514	0.8657	-0.4514	-0.4657
115	0.30	0.4276	0.4295	-0.1276	-0.1295
116	0.30	0.0086	0.0064	0.2914	0.2936
117	0.50	0.6390	0.6437	-0.1390	-0.1437

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
118	0.10	0.3982	0.3568	-0.2982	-0.2568
119	0.25	0.2733	0.2518	-0.0233	-0.0018
120	0.10	0.6840	0.6634	-0.5840	-0.5634
121	0.30	0.8046	0.8139	-0.5046	-0.5139
122	0.30	0.4539	0.4485	-0.1539	-0.1485
123	0.20	0.0243	0.0186	0.1757	0.1814
124	0.05	0.0480	0.0412	0.0020	0.0088
125	0.20	0.4310	0.4119	-0.2310	-0.2119
126	0.80	0.1250	0.0911	0.6750	0.7089
127	0.40	0.2246	0.2461	0.1754	0.1539

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
128	0.35	0.1533	0.1498	0.1967	0.2002
129	0.30	0.6206	0.6608	-0.3206	-0.3608
130	0.25	0.1368	0.1406	0.1132	0.1094
131	0.50	0.8299	0.8431	-0.3299	-0.3431
132	0.60	0.9180	0.9296	-0.3180	-0.3296
133	0.50	0.1231	0.1257	0.3769	0.3743
134	0.05	0.4034	0.3604	-0.3534	-0.3104
135	0.25	0.0892	0.0788	0.1608	0.1712
136	0.20	0.7816	0.7860	-0.5816	-0.5860
137	0.25	0.1290	0.1220	0.1210	0.1280

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
138	0.20	0.4870	0.4754	-0.2870	-0.2754
139	0.30	0.2283	0.2207	0.0717	0.0793
140	0.10	0.2222	0.1670	-0.1222	-0.0670
141	0.30	0.1698	0.1559	0.1302	0.1441
142	0.20	0.1530	0.1600	0.0470	0.0400
143	0.25	0.0228	0.0192	0.2272	0.2308
144	0.10	0.1101	0.1031	-0.0101	-0.0031
145	0.90	0.9137	0.9297	-0.0137	-0.0297
146	0.60	0.8640	0.8758	-0.2640	-0.2758
147	0.40	0.5814	0.5931	-0.1814	-0.1931

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
148	0.30	0.1342	0.1220	0.1658	0.1780
149	0.25	0.2422	0.2289	0.0078	0.0211
150	0.25	0.1084	0.0996	0.1416	0.1504
151	0.85	0.6429	0.6909	0.2071	0.1591
152	0.30	0.6328	0.6145	-0.3328	-0.3145
153	0.30	0.2804	0.2590	0.0196	0.0410
154	0.60	0.7636	0.7703	-0.1636	-0.1703
155	0.50	0.0240	0.0163	0.4760	0.4837
156	0.60	0.4884	0.5102	0.1116	0.0898
157	0.25	0.1706	0.1340	0.0794	0.1160

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
158	0.50	0.8654	0.8804	-0.3654	-0.3804
159	0.75	0.6626	0.6695	0.0874	0.0805
160	0.50	0.7529	0.7492	-0.2529	-0.2492
161	0.15	0.4464	0.4386	-0.2964	-0.2886
162	0.50	0.2176	0.1980	0.2824	0.3020
163	0.30	0.1645	0.1726	0.1355	0.1274
164	0.15	0.8167	0.8274	-0.6667	-0.6774
165	0.40	0.6849	0.6861	-0.2849	-0.2861
166	0.80	0.2929	0.3236	0.5071	0.4764
167	0.30	0.1602	0.1355	0.1398	0.1645

Appendix Table E3: (Continued)

Participant	(A) Participant estimate of $P(H_1 D_1, \dots, D_4)$	(B) Naïve Bayes' classifier estimate of $P(H_1 D_1, \dots, D_4)$	(C) Quantum Bayes' Conjecture estimate of $P(H_1 D_1, \dots, D_4)$	Difference $(A) - (B)$	Difference $(A) - (C)$
168	0.20	0.0591	0.0567	0.1409	0.1433
169	0.35	0.4364	0.4202	-0.0864	-0.0702
170	0.05	0.3670	0.3401	-0.3170	-0.2901
171	0.15	0.4394	0.3981	-0.2894	-0.2481
172	0.50	0.2959	0.2902	0.2041	0.2098
173	0.60	0.0975	0.0923	0.5025	0.5077
174	0.40	0.7990	0.8143	-0.3990	-0.4143
175	0.20	0.5794	0.5728	-0.3794	-0.3728